# Automatic Classification of Spatial Signatures on Semiconductor Wafermaps

Kenneth W. Tobin
Shaun S. Gleason
Thomas P. Karnowski
Oak Ridge National Laboratory
P.O. Box 2008
Oak Ridge , TN 37831-6011


Susan L. Cohen
Fred Lakhani
SEMATECH, Austin, Texas

MASTER

## DISCLAIMER

**Portions of this document may be illegible
in electronic image products. Images are
produced from the best available original
document.**

# Automatic Classification of Spatial Signatures on Semiconductor Wafermaps

Kenneth W. Tobin[a], Shaun S. Gleason, Thomas P. Karnowski
Oak Ridge National Laboratory[b], Oak Ridge, Tennessee
Susan L. Cohen, Fred Lakhani
SEMATECH, Austin, Texas

## ABSTRACT

This paper describes Spatial Signature Analysis (SSA), a cooperative research project between SEMATECH and Oak Ridge National Laboratory for automatically analyzing and reducing semiconductor wafermap defect data to useful information. Trends towards larger wafer formats and smaller critical dimensions have caused an exponential increase in the volume of visual and parametric defect data which must be analyzed and stored, therefore necessitating the development of automated tools for wafer defect analysis. Contamination particles that did not create problems with 1 micron design rules can now be categorized as killer defects. SSA is an automated wafermap analysis procedure which performs a sophisticated defect clustering and signature classification of electronic wafermaps. This procedure has been realized in a software system that contains a signature classifier that is user-trainable. Known examples of historically problematic process signatures are added to a training database for the classifier. Once a suitable training set has been established, the software can automatically segment and classify multiple signatures from a standard electronic wafermap file into user-defined categories. It is anticipated that successful integration of this technology with other wafer monitoring strategies will result in reduced time-to-discovery and ultimately improved product yield.

**Keywords:** Semiconductor, spatial signature, automatic inspection, wafermap analysis, pattern recognition, fuzzy classifier, classifier training

## 1. INTRODUCTION

Automated analysis of semiconductor wafer defect data has become increasingly important over the past several years as a means of quickly understanding and controlling contamination sources and process faults which impact product yield. This paper discusses the automatic analysis of defect distributions on semiconductor wafers as sensed by in-line optical inspection tools.

### 1.1 Spatial Signature Analysis

Trends towards larger semiconductor wafer formats and smaller critical dimensions have caused an exponential increase in the volume of visual and parametric defect data that must be analyzed and maintained by the semiconductor device manufacturer. This explosion in the volume of data has necessitated the development of automation tools for wafer defect analysis[1]. It has been estimated that up to 80% of the yield loss in the production of high-volume, very-large-scale integrated (VLSI) circuits can be attributed to random visual pattern defects[2]. Contamination particles that did not create problems with 1 $\mu$m design rules can now be categorized as "killer defects" as critical dimensions dip below 0.25 $\mu$m, i.e., defects which result in improper electrical device function. Spatial Signature Analysis (SSA) is an automated procedure that has been developed by the authors to address the issue of intelligent data reduction while

providing timely feedback on current manufacturing conditions. SSA performs a sophisticated defect clustering and signature classification of electronic wafermaps that represent visual pattern and particle defects[3].

Optical inspection of semiconductor wafers has long been the primary means of detecting the sources of wafer defects. Semiconductor yield engineers use high resolution images of individual defects collected off-line to assess problems in the manufacturing process. Since high-resolution off-line defect review is time consuming and expensive, process engineers also use low resolution defect wafermaps from in-line optical inspection tools to determine the potential source of problems in the manufacturing process. They accomplish this by analyzing and sourcing unique spatial distributions or "signatures" of defects on the wafer surface. Figure 1 shows an example of a high-resolution optical defect and several wafermaps containing various spatial signatures. Even when these spatial signatures do not contain significant portions of killer defects, they provide a diagnostic window into the manufacturing process. SSA attempts to emulate this process and to provide the fab engineer with faster time-to-results and enhanced yield management.
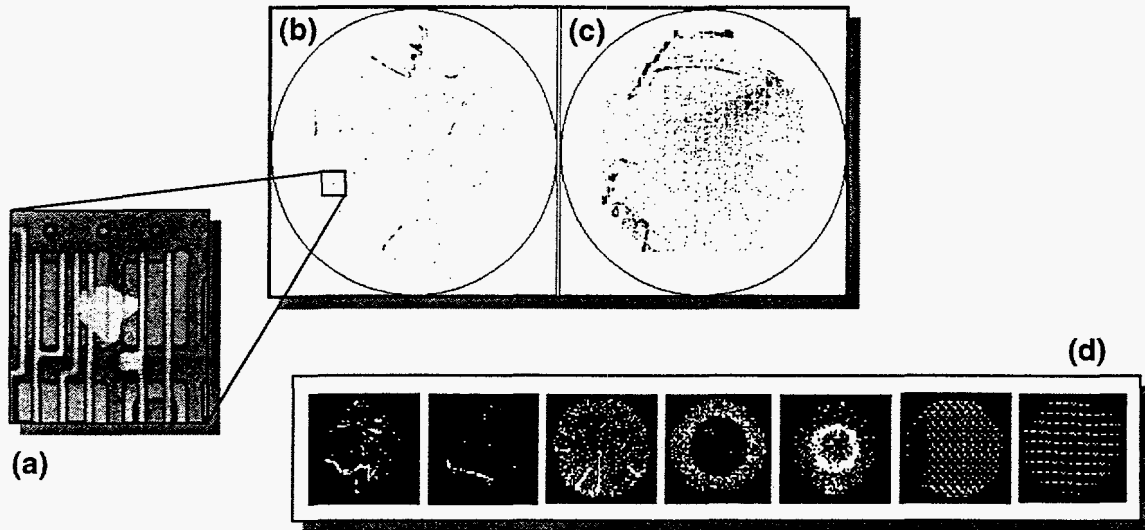


**Figure 1** - Examples of wafermap defects and signatures with (a) showing a high resolution optical image of a defect taken from a distribution of defects on a single wafer (b). The map shown in (c) consists of a composite, or "stack", of wafermaps while (d) shows several examples of various signatures which are indicative of manufacturing problems.

## 1.2 Automatic Signature Classification

SSA automatically collects defects on a wafermap that come from a single manufacturing source. A user-trained classifier assigns a label which identifies the root problem. For clarity of nomenclature in the following description of the procedure these definitions apply: wafermap defects (e.g., collected by a KLA or Tencor optical tool) are organized by SSA into "clusters"; clusters are grouped into "objects", such as a multi-element scratch composed of several small disconnected clusters; objects are then assigned to "sets", to distinguish curvilinear objects from compact objects for example; and finally objects in these sets are formed into "signatures" which are groups of objects that may be distributed across the wafer but which come from a single manufacturing source, e.g., multiple streaks in a "wagon wheel" pattern from a spin coating process.

SSA begins the signature classification process by converting the electronic wafermap file into a grey-scale image where each pixel is assigned an intensity value according to the number of defects in the subtended area. Each pixel represents a first-level clustering of the individual defects. Clusters of pixels, denoted as "objects", in this density image are connected into multi-element objects (e.g., a multi-element scratch) by means of a sophisticated clustering procedure. Objects are grouped into high-level "sets" depending on their proximity to neighboring clusters and on their morphology[4,5]. These defined sets are the result of a "divide and conquer" approach to the SSA problem required to

reduce the complexity of signature classification. There are four distinct and fundamental sets in use with the SSA procedure denoted by global, curvilinear, amorphous, and micro-structure. The assumption is made that every tightly clustered or distributed object, i.e., an element of a process signature, can be categorized into one of these fundamental sets.

Each set is characterized individually, i.e., objects belonging to each set have unique descriptive features which relate to the set. For example, elongated objects such as scratches or streaks are assigned to the curvilinear set since they have curvilinear attributes such as elongation, compactness, orientation, etc. These objects tend to be associated with mechanical wafer damage. Tightly clustered objects are placed in the amorphous set and can generally be associated with problems such as insufficient etching, or other systematic sources which deposit large clusters of defects on the wafer surface that are not related to mechanical damage. Distributed objects such as a ring pattern or a random uniform distribution of particles which are broadly distributed over the wafer surface are grouped into the "global" set. Global objects generally consist of sparsely distributed defects and have no highly clustered components yet are treated as one wafermap object since they arise from a single source. Micro-structure objects define the final set. These objects are composed of a distribution of pixels whose sub-pixel defects are organized in a linear fashion. These pixel-level objects arise from planarization processes such as Chemical Mechanical Polishing (CMP) and are also associated with mechanical damage to the wafer surface but on a micro-scale relative to objects in the curvilinear set.

The attributes, or features, used to distinguish globally distributed events and distributions of microstructure clusters are centralized geometric moments[6,7], while the features used to describe curvilinear or amorphous objects are morphological, e.g., size, location, elongation, compactness, etc.. These features give a unique description of the defect populations represented on the wafer surface and provide a means for automatic classification. Figure 2 shows several SSA processed wafermap results for random systematic and mechanically imparted signatures. Figure 2 (a) shows a random particle distribution, and (b) a systematic particle distribution in a ring pattern. Both signatures are globally distributed across the wafer surface. Figure 2 (c) shows a scratch-type signature while (d) shows a streak signature. Note that the scratch and streak signatures are both curvilinear events but that the scratch contains one elongated object while the streak contains several distributed and disconnected objects.
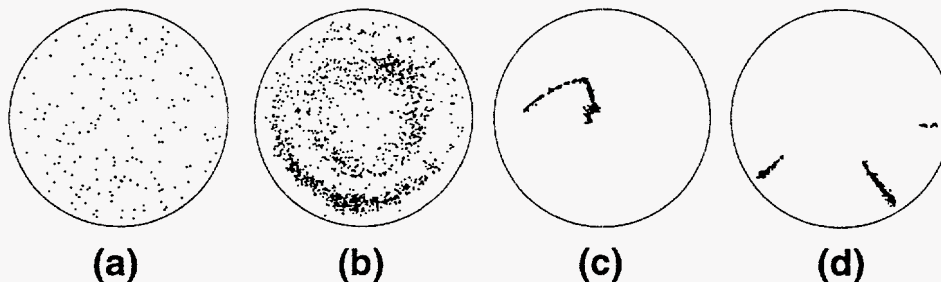


**(a)**  **(b)**  **(c)**  **(d)**

**Figure 2** - Examples of wafermap signatures found by SSA with (a) and (b) showing random and systematic particle distributions (global set), and (c) and (d) showing mechanically imparted signatures, e.g., scratch and streak respectively (curvilinear set).

Once an object has been assigned to a high-level set and characterized, its features are sent to a classifier where a user-defined label is assigned to the result. For this work, a pair-wise fuzzy k-Nearest Neighbor (kNN) approach has been adapted[8,9] which uses a unique feature reduction procedure to optimize classifier performance[10]. For industrial pattern recognition problems, it has been our experience that non-parametric classifiers such as nearest-mean or kNN[11] apply well. Such classifiers do not require information about the statistical distribution of features. It is difficult to ascertain a statistical parameterization for the large variety of class types encountered. Furthermore, in an industrial setting, it is often required that the classifier system begin to classify new data with few training examples. Bayesian classifiers[12] and neural networks[13] can also work well but generally require large sample populations to estimate the appropriate statistics for their method and would therefore be difficult to implement for this application. This is primarily due to the diverse nature of the patterns that arise for different manufacturing processes and processing facilities coupled with the length of time required to collect large sample populations. Also, over the period of time required to collect large sample sets, acceptable process variations can occur which confuse the boundaries between classes. The pair-wise fuzzy

kNN classifier training set can readily be maintained over time (e.g., by including and excluding examples based on time and date), and can operate adequately with relatively few examples for each class.

The remainder of this paper focuses on the classifier method used for effective sourcing of wafermap signatures. The classifier assigns labels to process signatures which are indicative of the source of the problem. The system is trained and maintained by the user and is therefore required to provide useful feedback to the user. The system also assists the user in locating and mitigating confusion which may arise within the training data. An automatic classification system must demonstrate these basic properties if it is going to be used with confidence in the manufacturing environment.

## 2. SSA CLASSIFIER

A fuzzy kNN classifier has been adapted to perform a pair-wise classification of an unlabeled signature so that a process-specific label can be assigned. The classifier uses example signatures which are stored in a prototype signature library (PSL). The PSL is established and maintained by the user and contains various examples of signatures that are associated with the manufacturing process being monitored. Figure 3 shows the PSL software interface which the user uses to manage the classifier training data and to obtain information on the expected performance of the system in the field. Information is also provided to the user to assist in the elimination of ambiguity, or confusion, in the training data to improve performance.

Each high-level set in the PSL (i.e., global, curvilinear, amorphous, and micro-structure) contains its own set of training data and therefore constitutes a separate classifier within the SSA system. The software automatically tracks the signature's high-level set so that the user does not need to consider this during training. There are several advantages to using the set hierarchy for signature classification. A signature is classified based on measured features, or attributes, that succinctly describe the event. Each high-level set can be described using different attributes. For example, signatures in the global set, which contains distributions of defect data over the entire surface, are well described using geometric moments. Signatures in the curvilinear set are better described according to morphological features such as location, elongation, and compactness. This ability to uniquely describe the signature event associated with each set gives SSA the ability to classify a broad variety of signature types within one system.

The set structure also enhances classification reliability by separating the decision space into four mutually exclusive regions. While the number of training data samples required for the system may be large in total, each set contains, to a rough approximation, one quarter of the data and one quarter of the defined classes. The classifier for any given high-level set is reduced in the number of labels it can assign which reduces the decision complexity per set and increases performance. Also, the pair-wise classifier implementation requires on the order $N(N-1)/2$ calculations per classification, where N is the number of defined classes in one of the four sets. If the hierarchy of sets was not used then the equivalent number of calculations would be on the order $2N(4N-1)$ which equates to a sixteen-fold computational increase. Therefore by using the indicated set strategy, a broad variety of signature types can be labeled by the system and both classification performance and computational performance are improved.

### 2.1 Fuzzy Measurements and Class Ambiguity

The SSA classifier assigns a fuzzy membership value to the unlabeled signature which provides the system with information suitable for estimating the confidence of the decision. The fuzzy membership describes what portion of an unlabeled signature resides in each of the defined classes. If the membership is relatively high for two classes and low for three others, then there is a clear delineation between the first two classes and the other three, but there is confusion within the first two classes. This data becomes important when ultimately assigning a crisp label to the signature. For example, the classifier might assign a signature membership 0.8 to "scratch", 0.75 to "streak", 0.2 to "double-slot", and 0.01 to "stain". For this situation the signature would likely belong to "scratch" or "stain", but the ambiguity between the two would be high making a crisp assignment difficult.
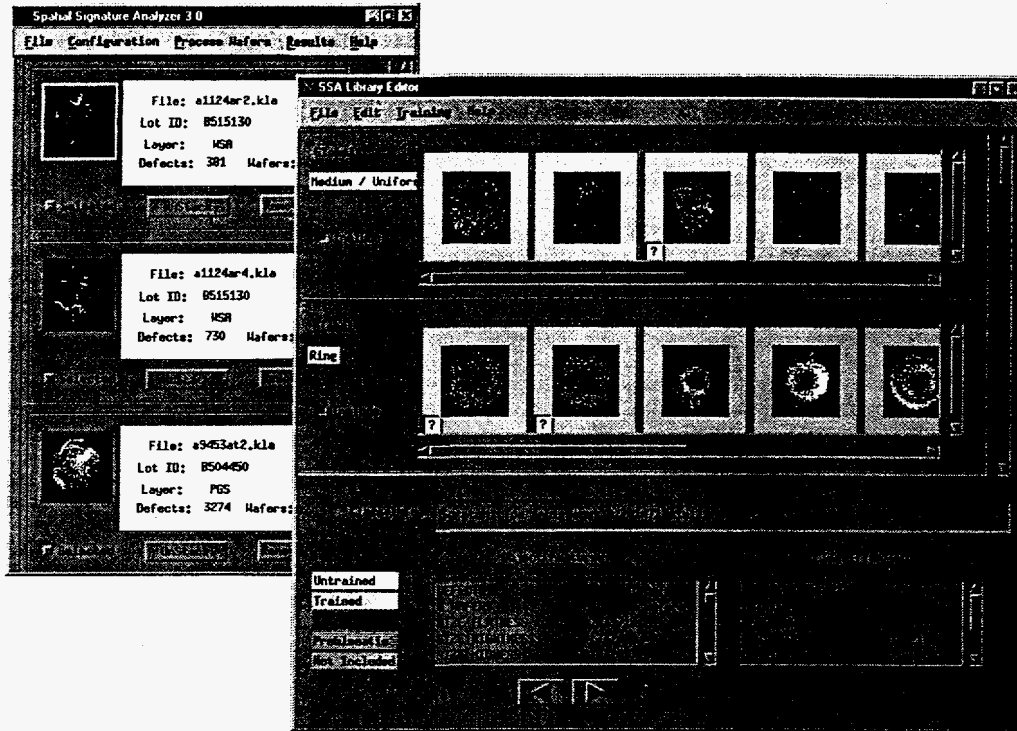
**Figure 3** - Example of the interface developed to demonstrate and test the SSA technology. The screen on the left is the main window where the user brings in wafermap files for analysis. The screen on the right shows the prototype signature library window where the user stores examples and maintains the training database.

One method of handling this confusion is to accommodate a class of "unknown" signatures. One of the benefits of using a fuzzy system is that the signature can be assigned to the category "unknown" which , in certain situations, may provide a much greater advantage over crisply assigning the signature to the wrong category. The SSA classifier uses the training data and the subsequent fuzzy information derived from it, to dynamically set a "defuzzification" threshold which accommodates labeling data as "unknown". The defuzzification level is controlled by the user specifying how much an incorrect decision is "worth" to the process. From an economic standpoint, some classes of signatures may cost more in potential yield loss and would therefore require a high probability of assignment to the correct or the "unknown" category rather than to an incorrect class which may be of lesser economic importance. The user therefore sets a level of class worth prior to training. This is achieved by allowing an "unknown" decision to count in part towards a correct decision. For example, if the user sets a worth-value of 60%, then 60% of a signature placed in the "unknown" category will count towards a correct decision during training. To understand the effect of this value, if a value of 0% is prescribed during training, then the classifier will always assign a signature to one of the defined classes. If a value of 100% is prescribed, then all the signatures will be assigned to the "unknown" class. Setting this value between 0% and 100% lets the classifier identify signatures with ambiguous memberships by assigning them to the "unknown" category.

## 2.2 Training the Classifier

The user begins the training process by adding representative signatures to the PSL with the SSA results window. After an interesting result is found by the SSA advanced clustering process, the user selects the signature with a mouse click and adds it to the library. Once the library is populated, the user selects the "Training" option from the PSL menu (see Fig. 3). Each set is trained independently of the others such that if only one set has recently been modified by the user through the insertion, deletion, or relocation of a signature, then only that set will be retrained. Note that training is the most time consuming aspect of the classification procedure. It may take several minutes to perform training on any one

of the sets and this time increases according to N(N-1)/2 as the number of classes, N, increases. The time required is linear with an increase in the number of examples. This has not proved to be a major issue to date since training takes place only occasionally and is performed off-line. Once a classifier has been trained for each set, the process of classifying a new unlabeled signature is very fast, i.e., on the order of < 1sec.

The training algorithm for the fuzzy classifier determines a number of parameters from the example data which are used to automatically optimize several algorithm parameters (e.g., the defuzzification level is determined based on the "worth" parameter defined by the user and the nature of the data in the library). The method uses a hold-one-out technique[8] (HOO) to estimate the expected performance of the classifier in the field. The HOO expected performance is determined by holding out an example point, training the set, and then classifying the held out point. The process is continued until all the examples in the training data have been held out once. The resulting statistics give an approximation to the expected performance of the classifier or unknown data points. A fuzzy measurement of ambiguity based on an "index of fuzziness"[14] is determined during this process for each defined class in the set. It is typically observed that the expected performance based solely on the HOO metric tends to be high. A more conservative expected performance estimate is made by using the class ambiguity measure in the feature SSA reduction process as described in the reference [10]. The ambiguity of a class is represented numerically by a number in the range [0,1] with 0 meaning there is no ambiguity (or conflict) between a given class and all others while a value of 1 indicates severe conflict.

The training algorithm automatically determines which signature features are required to distinguish one class from the next within the set[10]. This novel technique results in higher performance from the classifier by reducing the complexity of the matching problem. For example, the number of features used to describe a global signature are 25 geometric moments and 3 non-moment features for a total of 28 features. When comparing a "ring" to a "uniform" distribution it may only require a few features to differentiate the two. When comparing a "ring" to a "skew" it may require different features. Usually, only a few of the 28 features are required to differentiate any given pair of classes in the global set. It has been shown[10] that the classifier performance will degrade as more and more non-discriminating features are considered.

Table I shows an example of training result statistics for a set of global data shown (partially) in Fig. 4. This data will be further described in the following section.
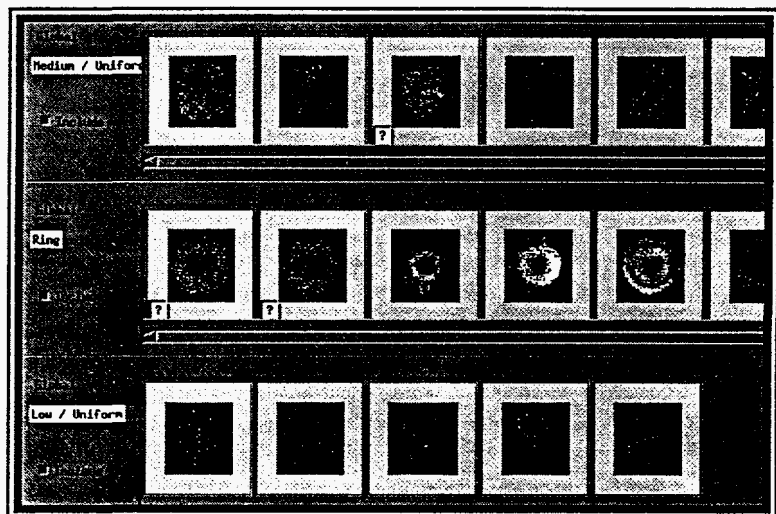


**Figure 4** - A partial set of global data used to demonstrate the statistical and fuzzy parameters of the set obtained during training. Table I shows the corresponding training results data.

### 2.3 Training Feedback and Results

One of the most important requirements of an automatic classification system is feedback to the user about the quality of training data. In general, the inner workings of a classification system can be very complex. The procedure used to classify signatures for SSA develops a substantial amount of information which relates to the capability of the classifier and the quality of the training data. This section discusses the procedure developed through this research to help the user quickly determine, locate, and correct conflicts in the data to improve classifier performance.

As mentioned in the previous section, there are several values returned from the classifier training algorithm which give the user information on expected performance. A fuzzy system also provides an opportunity to supply important feedback to the user on the quality of the data in the training set. For example, from the data in Table I, it is apparent that there is some confusion in the data between the sets "Medium/Uniform" and "Ring". The ambiguity for these two classes is relatively high compared to the other classes (except for "Low/Uniform") and the performance is lower than the other sets. The PSL library interface has been designed to provide the user with a display of alpha-numeric and color codes that can be used to quickly ascertain the source of the conflict. When a training session has been completed, all of the signature map icons in the PSL are color coded to represent the following conditions:

| TABLE I Example of training results for the global set data shown in Fig. 4 | | | | |
|---|---|---|---|---|
| Class | No. of Examples | Ambiguity | Class Performance | Set Performance |
| Medium/Uniform | 9 | 0.13 | 89% | 93% |
| Ring | 10 | 0.18 | 80% | |
| Low/Uniform | 5 | 0.17 | 100% | |
| Sparse/Random | 8 | 0.00 | 100% | |
| Semi Ring | 8 | 0.01 | 100% | |
| Excluded | 5 | 0.00 | 100% | |

**Yellow**      indicates that the class has high expected performance and that the class ambiguity is low,

**Orange**      indicates that the class has either low expected performance or high ambiguity or that not enough examples exist in the library for that class to be statistically significant,

**Grey**      indicates that the user has deselected the class so that it will not be considered in the training set,

**"?"**      if an individual example has a higher fuzzy membership to another class, or if its membership is below the defuzzification level (indicating that it would be classified as "unknown") a question mark is placed in the signature icon.

Textual information is also provided to the user based on the expected performance and ambiguity (e.g., "Ring class is problematic: performance is low") but to take this one step further, the fuzzy membership values for the data are used to determine a measure of subsethood[15]. The subsethood measure of a fuzzy set can be used to pinpoint the set, or sets, that the data looks most similar to, i.e., is a subset of. The subsethood measure is a value in the range [0,1] where 0 indicates no similarity to another set while 1 indicates absolute similarity. Subsethood is used to present information to the user such as "Scratch is problematic: looks 0.7 similar to streak".

Note that a class could still produce good expected performance and low ambiguity even if there are some questionable examples in it. The user has the option of adding, deleting, or moving signatures to improve expected performance. The user can also temporarily deselect a class from the library until the conflict between it and another is better understood and can be resolved. For example, if a class was coded as problematic (i.e., "orange") due to an insufficient number of samples in the library, the user could temporarily deselect it but continue to add new examples to that class. Once sufficiently populated it could be re-selected and used for training.

Figure 5 shows the data from Fig. 4 after three potentially problematic signatures have been removed. Notice in Fig. 4 that there are three signatures marked with the "?" symbol, one in the "Medium/Uniform" class and two in the "Ring" class. Although the performance for these two classes is reasonable, i.e., 89% and 80% respectively (see Table I), there is some similarity between the classes which can be reduced by moving or deleting these signatures. Note that the two problematic "Ring" signatures in Fig. 4 look very similar ro the "Medium/Uniform" class examples. Also notice that the problematic "Medium/Uniform" signature looks somewhat like a "Ring" signature. For the purpose of demonstrating the ability to improve the expected performance, these three signatures have been removed (see Fig. 5) and the classifier retrained. Table II shows the class and set performance statistics for the modified PSL. Note that the class performance for "Medium/Uniform" and "Ring" have increased from 89% to 100% and 80% to 98% respectively. In short, the two classes have been made more distinct.
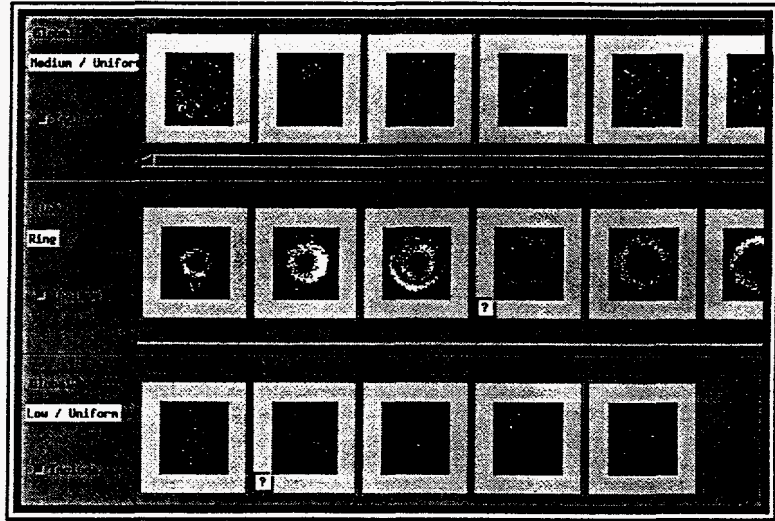


**Figure 5** - A modification of the global data shown in Fig.4. Table II shows the corresponding improved training results.

The wafermap data shown in this paper were collected from several of the SEMATECH member companies for the purpose of developing the SSA advanced clustering and classification procedures. While this data has been essential to the development of this technology, it is limited in its ability to qualify SSA for manufacturing applications. As will be described in the following section, a validation effort will be performed over the next several months which will demonstrate the efficacy of SSA in the manufacturing environment. Based on the data at hand, it is anticipated that the method will provide fast reliable and timely feedback on the state of the manufacturing process. Table III shows the expected results for a classifier trained with 113 examples of a large variety of signature examples distributed across a global, curvilinear, and amorphous set. These results demonstrate the classifiers ability to accommodate a wide variety of signatures, e.g., from globally distributed distributions such as those shown in Figs. 4 and 5 to scratches, streaks, clusters, and repetitive anomalies an. The expected performance for this training set is 94% overall while the set performance ranges from 84% to 99%, with

| TABLE II Example of training results for the modified global set data shown in Fig. 5 | | | | |
|---|---|---|---|---|
| Class | No. of Examples | Ambiguity | Class Performance | Set Performance |
| Medium/Uniform | 8 | 0.00 | 100% | 99% |
| Ring | 8 | 0.14 | 98% | |
| Low/Uniform | 5 | 0.17 | 96% | |
| Sparse/Random | 8 | 0.00 | 100% | |
| Semi Ring | 8 | 0.01 | 100% | |
| Excluded | 5 | 0.00 | 100% | |

several classes performing at an expected 100% accuracy. This example represents a 13-class problem with an average of 8.7 examples per class.

**TABLE III**
Example of training results for a three-set library which includes global, curvilinear and amorphous entries.

| Class | No. of Examples | Ambiguity | Class Performance | Set Performance | Total Expected (HOO) Performance |
|---|---|---|---|---|---|
| **Global Set** | | | | | |
| Medium/Uniform | 8 | 0.00 | 100% | 99% | 94% |
| Ring | 8 | 0.14 | 98% | | |
| Low/Uniform | 5 | 0.17 | 96% | | |
| Sparse/Random | 8 | 0.00 | 100% | | |
| Semi Ring | 8 | 0.01 | 100% | | |
| Excluded | 5 | 0.00 | 100% | | |
| **Curvilinear Set** | | | | | |
| Complex Scratch | 13 | 0.19 | 98% | 93% | |
| Simple Scratch | 10 | 0.42 | 82% | | |
| Streak | 20 | 0.27 | 92% | | |
| Excluded (C) | 8 | 0.00 | 100% | | |
| **Amorphous Set** | | | | | |
| Small Cluster | 7 | 0.56 | 83% | 84% | |
| Medium Cluster | 9 | 0.47 | 84% | | |
| Recipe Error | 4 | 0.00 | 100% | | |

## 3. CONCLUSION

The progress made to date on the SSA advanced clustering and signature classification procedure has been demonstrated to quickly reduce wafermap optical defect data to useful information. For an automatic classification system to be useful in the manufacturing environment, it is not only necessary that it provide reliable and believable information, but it must also provide feedback to the user on populating and maintaining the training data. The classifier can only perform as well as the representative signatures used to train it and the system must provide feedback to the user about ambiguity which may result in degraded performance. The SSA classifier has been demonstrated to provide both high expected performance and ease of training.

SSA research and development will be continuing throughout 1997. The first half of the year will be spent performing a test and validation of the technology at three separate manufacturing sites. The SSA code will be installed and run as a background process that will automatically monitor and analyze all wafermaps optically inspected with in-line tools during short-loop tests. These tests will limit the focus of SSA to three distinct and specific clusters of manufacturing processes and show the ability of the technology to quickly characterize manufacturing problems. The results of the validation exercise will be published later in the year.

During the second half of the year, research will begin to extend SSA to include non-optical wafermap data from electrical tests (e-tests) such as parametric, binmap, bitmap, etc.. These data types are also organized spatially across the wafer and are therefore amenable to automatic spatial analysis. It is intended that a method be developed which will correlate optical and e-test data so that improved knowledge can be obtained regarding the killing potential of various particle and pattern defect distributions.

SSA has the potential to provide automation of several defect-based monitoring processes. Figure 6 shows schematically in (a), the manufacturing and data sampling process, (b) the storage and management of process and product data, and (c) the analysis and sourcing of defect information to control manufacturing. Initially, it is anticipated that SSA will play a large role in automating the analysis of wafermaps to quickly source manufacturing problems based on common signature patterns. The dotted lines emanating from the"wafermap analysis"region in the figure represent
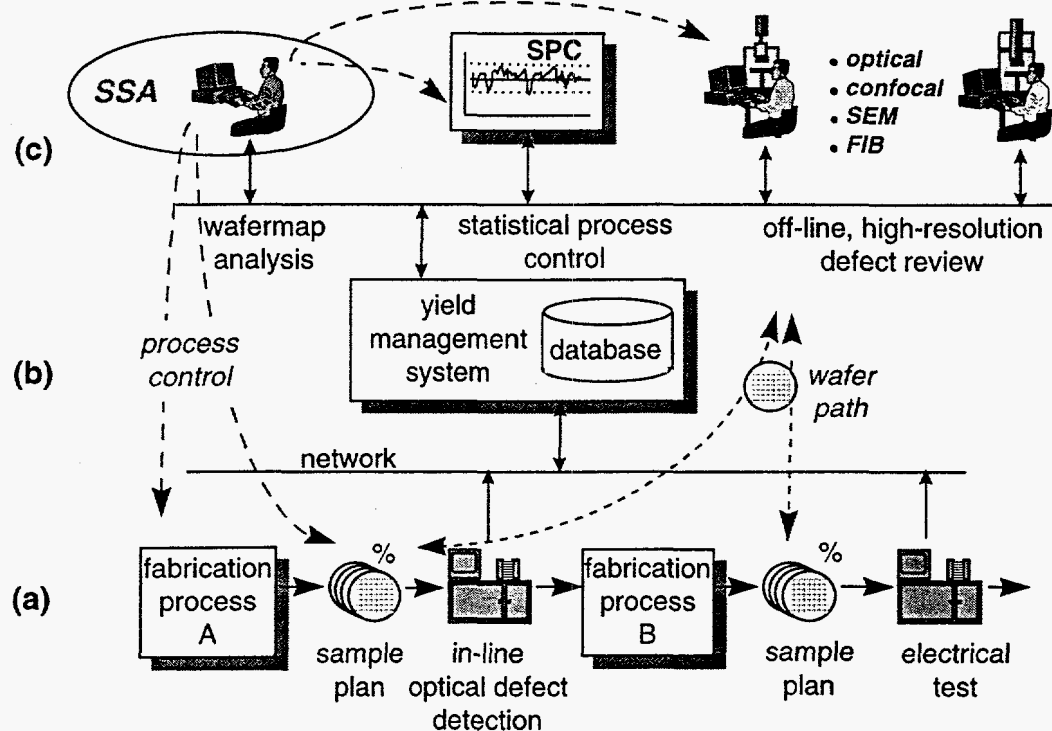


**Figure 6** - Schematic representation of (a) semiconductor manufacturing, (b) data storage and management, and (c) data analysis and defect sourcing.

functions that are monitored manually at present by yield engineers but that are amenable to automation by SSA. For example, the generation of the highly detailed SSA description will provide new information for statistical process control (SPC) e.g., counts of systematic or random distributions of particles, simple and complex scratches, streaks, clusters, and a variety of other signature types which are defined by the user through training. SSA will also result in a reduction in the number of wafers required for off-line review (i.e., optical, SEM, etc.). This is accomplished by automatically pre-qualifying defect data for review based on the signature type. For example, a mechanical scratch would likely not be reviewed off-line since the source can be readily determined from the signature class. Other defect distributions found by SSA may still require off-line review to locate the source of the particle contamination, but SSA can provide an efficient sampling plan based on the signature result which will reduce the number of sites which must be revisited. The result will be increased wafer throughput on these review tools.

In summary, it is anticipated that SSA will provide the manufacturer with a new level of information which is suitable for controlling the manufacturing process and quickly understanding and correcting important yield issues.

# REFERENCES

1.  H. Singh, F. Lakhani, P. Proctor, and A. Kazakoff, "Defect-Data Management System at SEMATECH", *Solid State Technology*, December, 1995.

2.  T. Hattori, "Detection and Identification of Particles on Silicon Surfaces", *Particles on Surfaces, Detection, Adhesion, and Removal*, Edited by K. L. Mittal, Marcel Dekker, Inc., New York, p.201.

3.  S. S. Gleason, K. W. Tobin, and T. P. Karnowski, "Spatial Signature Analysis of Semiconductor Defects for Manufacturing Problem Diagnosis", *Solid State Technology*, July, 1996.

4.  K. W. Tobin, S. S. Gleason, T. P. Karnowski, M. H. Bennett, "An Image Paradigm for Semiconductor Defect Data Reduction", *SPIE's 1996 International Symposium on Microlithography*, Santa Clara Convention Center, Santa Clara, CA, March 10-15, 1996.

5.  Gleason, S.S., and Tobin, K.W., "Directional-based Dilation for Connection of Piece-Wise Objects: A Semiconductor Manufacturing Case Study", *International Conference on Image Processing*, Lausanne, Switzerland, Sept 16-19, 1996.

6.  S. X. Liao, and M. Pawlak, "On Image Analysis by Moments", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 18, No. 3, March 1996, p.252.

7.  C. The, and R. Chin, "On Image Analysis by the Method of Moments", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 10, No. 4, July 1988, p.496.

8.  R. O. Duda, and P. E. Hart, *Pattern Classification and Scene Analysis*, John Wiley & Sons, New York, 1973, p.95.

9.  J. M. Keller, M. R. Gray, and J. A. Givens, Jr., "A Fuzzy K-Nearest Neighbor Algorithm", *IEEE Transactions on Systems, Man, and Cybernetics*, Vol. SMC-15, No. 4, p. 580, July/August 1985.

10. K. W. Tobin, S. S. Gleason, T. P. Karnowski, S. L. Cohen, "Feature Analysis and Classification of Manufacturing Signatures on Semiconductor Wafers", *SPIE's 9th Annual Symposium on Electronic Imaging: Science and Technology*, San Jose Convention Center, San Jose, CA, February 9-14, 1997.

11. K. Fukunaga, *Introduction to Statistical Pattern Recognition*, 2$^{nd}$ Ed., Academic Press, Inc., San Diego, 1990.

12. J. M. Bernardo and A. F. M. Smith, *Bayesian Theory*, John Wiley & Sons Limited, West Sussex, England, 1994.

13. S. Haykin, *Neural Networks: A Comprehensive Foundation*, Macmillan College Publishing Company, New York, 1994.

14. S. K. Pal, and B. Chakraborty, "Fuzzy Set Theoretic Measure for Automatic Feature Evaluation", *IEEE Transactions on Systems, Man, and Cybernetics*, Vol. SMC-16, No. 5, September/October 1986.

15. Y. Yuan and M. J. Shaw, "Induction of Fuzzy Decision Trees", A. I. Technical Report VIVC-BI-AI-DSS-94-OZ, University of Illinois of Urbana-Champaign, February 1994.

# DISCLAIMER