Semiconductor Defect Data Reduction for Process Automation and Characterization

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Semiconductor Defect Data Reduction for Process Automation and Characterization

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ABSTRACT

Automation tools for semiconductor defect data analysis are becoming necessary as device density and wafer sizes continue to increase. These tools are needed to efficiently and robustly process the increasing amounts of data to quickly characterize manufacturing processes and accelerate yield learning. An image-based method is presented for analyzing process “signatures” from defect data distributions. Applications are presented for enhanced statistical process control, automatic process characterization, and intelligent sub-sampling of event distributions for off-line high-resolution defect review.

KEY WORDS

semiconductor, automation, yield enhancement, defect detection, image processing, morphology, pattern recognition

INTRODUCTION

The continued trend in semiconductor manufacturing towards higher density devices and larger wafer formats is resulting in a greater need for automated yield analysis tools. The increased application of image-based defect detection and review workstations for process monitoring and characterization is generating considerable amounts of data for evaluation by production personnel. This data is necessary to evaluate the state of the manufacturing process and to ultimately improve product yield in a timely manner. Defect yield management tools are beginning to appear on the market which allow the user to archive and review various permutations of semiconductor defect wafermaps and high-resolution defect image data, but to date their ability to automatically recognize and classify anomalous patterns in the data have been limited. These anomalous patterns represent "signatures" of the process equipment or process steps used in manufacturing. Automatic signature recognition can lead to efficient process characterization and faster yield learning.

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The focus of this research has been on developing automated methods for detecting and classifying patterns, or process signatures, based on low-resolution (e.g., 0.5 μm/pixel) optical wafermap defect distributions. Figure 1 shows a scenario for collecting and analyzing defect data in a production environment. As wafers exit a fabrication process (e.g., fabrication process A below) wafermap data is generated by an in-line defect detection workstation generally incorporating a microscopy or light-scattering system. A sampling plan is implemented which encompasses a small percentage of a batch or “lot” of wafers (e.g. 20% of wafers in a given lot). Once a wafer has been scanned by the instrument, its electronic wafermap is moved to a yield management system which includes a database where some level of automatic statistical process control (SPC) may be used to count “events”. Events are occurrences on the wafer which were sensed by the in-line defect detection tool and may arise from particle contamination, mechanical damage, process variations, or process excursions. The SPC analysis attempts to count events and develop trend data which can be used for prediction or to alarm operators when a process is going out of specification or when maintenance or calibration must be scheduled.

A smaller percentage of the wafermap data (e.g. 20% of the SPC sampling plan, or one lot out of every five lots) will be manually inspected unless SPC requires otherwise. The information in the wafermap consists of detected defect coordinates as well as process information such as step, layer, and product. The existence of patterns in the wafermap data is typically observed manually by an operator viewing a plot of the coordinate points during analysis. The wafermap data may be combined or "stacked" across wafers in a lot or across lots to better view the evolution of process signatures which may assist in...
diagnosing manufacturing problems that may be too subtle on a per wafer basis. Also, a subsample plan may be developed during manual wafermap analysis prior to off-line, high-resolution defect review. Off-line review takes place on a microscopy workstation and attempts to classify the defect (i.e., discern the exact type and cause of the defect) by viewing, at high resolution (e.g., 0.01 μm/pixel), individual defect morphology, color, texture, or relationship to process or layer (e.g., extra-pattern due to an insufficient etch or lithography problem). Typically, a coordinate map may contain several hundred to several thousand defects which must be manually reviewed and classified during off-line review. Consider an event such as a large scratch that may contain hundreds of individually detected defects all originating from the same cause. A pre-analysis of signatures on the wafermap can result in an efficient high-resolution sampling plan which greatly reduces the number of defects which must be manually revisited.

The ability of existing analysis tools to segment events into categories such as “random”, “scratch”, or “stain”, are extremely limited, yet these patterns are clearly discernable to a trained operator in wafermap displays and their association with process conditions are well documented 3. Figure 2 shows an example of a single wafermap defect distribution plot and a map developed by stacking several wafermaps together. Automation tools for wafermap analysis currently use simple nearest-neighbor clustering techniques to group data primarily into “random” or “grouped” events but specific classifications are not obtained. Groupings relating the proximity of large objects to other connected groups or events (a “forest” versus “trees” approach) are not performed outside of this work. The automatic grouping of events into process-related categories can improve the performance of SPC techniques currently in practice, reduce the requirements for manual wafermap evaluation, and supply the necessary information to intelligently subsample the wafer coordinate distribution for efficient off-line, high-resolution defect review and classification.

Fig. 2 - Wafermap defect data distributions for (a) a single map showing various random and scratch events which, and (b) a stack, or composite, of maps showing radial artifacts and a skewed particle contamination.
AUTOMATED PROCESS SIGNATURE ANALYSIS

The automated analysis of wafermap data to segment and characterize process events can be considered as a "data-to-information" process as represented in Fig. 3. The manufactured defect is the base piece of data which is sensed, organized, and represented through the electronic wafermap. This data is processed using statistical and morphological imaging techniques, as described in the next section, to segment and provide information about the current state of manufacturing. This "information" can be further extrapolated to reveal process knowledge by associating the signature with true process variables and conditions which have been used to train a spatial signature analysis (SSA) system over an extended period of time. This is the ongoing goal of the current research and will be achieved in a demonstratable sense by the end of this calendar year. Towards this end, an SSA software tool has been developed by the researchers as a platform for development and testing of the SSA concepts.

The current SSA software tool provides an automatic segmentation of defect coordinate data into separate events, such as a separation of random unconnected events from scratch events. The tool consists of a C/C++ software library and a graphical user interface (shown in Fig. 4) currently compiled for a UNIX platform. Input to the tool is provided from industry standard electronic wafermap file formats or can be directly interfaced with yield management systems currently in use. Typically there are several competing or overlapping events which may exist on a wafermap or stack. The current analysis tool separates these data into high-level groups which fall naturally into familiar categories for the fabrication personnel. Measurement features (e.g., shape, extent, location, proximity to other events, etc.) are extracted from these segmented events for use in signature classification and process association. The SSA

Fig. 3 - Data-to-information process flow for automated semiconductor spatial signature analysis.

Fig. 4 - Interface for the Oak Ridge National Laboratory SSA Tool
tool produces a results file which clusters the defect data into high-level connected and random events, and tabulates object feature measurements which will be used for further grouping, e.g., grouping long unconnected scratch objects into single objects, and for object and signature classification, i.e., associating connected object events with human-level descriptions of process issues.

STATISTICAL AND MORPHOLOGICAL IMAGE PROCESSING

The fundamental premise behind the approach described in this work is that wafermap defect data can be evaluated using image processing techniques which emulate the visual grouping and shape analysis performed by human inspectors during defect review. To achieve this goal, the wafermap is initially converted to an image where each pixel intensity value represents the number of defects per unit area. This technique of applying a “quadrature” mapping (i.e., binning) of the defects into a density image has been used in the past to primarily analyze random event distributions with Poisson statistics. This approach was limited in that it required a fairly coarse sampling of the defect map to ensure smoothly varying statistical properties across the wafermap (e.g., a 32 x 32 grid with a sample size of (Δx,Δy) = 6,250 μm for a 200 mm wafer), and the approach was only applicable to random event distributions (e.g., particle contamination) as opposed to anomalous discrete events such as stains or scratches.

In the current work, a fine-scale defect map is generated (e.g., 512 x 512 pixels, representing a sample size of (Δx,Δy) =390 μm for a 200 mm wafer). Figure 5 represents the process flow used for the current work. A grey-scale density image, $p(x,y)$, is generated from the electronic wafermap for processing. This image is initially parsed into low density, unconnected events to segment random events from other events. The remaining events image is binarized and operated on by a series of morphological processes which account for nearest-neighbor relationships as well as the relationship between large connected groups, i.e., the “forest and trees” concept described earlier. Random event
objects from the initially segmented image are then re-evaluated to determine if some should be merged with the large connected objects image. The result of morphological analysis is two binary masking images (e.g., Fig. 6) denoted \( M_1(x,y) \) and \( M_2(x,y) \) which will segment the original density image into two separate connected group results, i.e.,

\[
p_1(x,y) = M_1(x,y) \cdot p(x,y), \quad p_2(x,y) = M_2(x,y) \cdot p(x,y)
\]

where \( p_1(x,y) \) and \( p_2(x,y) \) represent long connected regions and compact regions respectively. The final random event density image is determined by taking the compliment of \( M_1(x,y) \land M_2(x,y) \) multiplied by the original density, i.e.,

\[
p_{\text{r}}(x,y) = \overline{M_1(x,y) \land M_2(x,y)} \cdot p(x,y)
\]

It should be noted that \( p(x,y) = p_{\text{r}}(x,y) + p_1(x,y) + p_2(x,y) \).

Once the random event image and connected event images are determined, a number of features are measured. From the random events image, \( p_{\text{r}} \), group statistics are measured which reveal information about the total, quadrant, radial, or annular density, or moment statistics such as skew or kurtosis. From the connected objects image, \( p_1 \) and \( p_2 \), features such as area, elongation, compactness, proximity, etc. are determined. The objects and their features are managed in the software structure such that each individual defect coordinate from the original wafermap can be associated with an object event, which is necessary, for example, to develop an intelligent subsampling plan for off-line defect review.

![Fig. 6 - (a) Original wafermap image \( p(x,y) \), (b) long connected regions mask, \( M_1(x,y) \), and (c) compact regions mask, \( M_2(x,y) \).](image)

Figure 7 shows an example result from the process described above. Image (a) in the figure represents the original wafermap display of defects which must be segmented into constituent components.
Image (b) contains the random events typically associated with particle contamination. Images (c) and (d) contain segmented object groups associated with large and compact connected events respectively such as the radial signature shown.

APPLICATION TO STATISTICAL PROCESS CONTROL

Referring once again to Fig. 1, a percentage of wafers are typically scanned in-line from each lot as it completes a given fabrication process or a group of processes. Due to the large number of wafers traveling through a plant at any given time, manual evaluation of all data is not feasible. For many fabrication situations, this in-line wafermap data will be processed automatically to provide SPC control data in the form of, for example, trend charts. These control charts will plot the number of events detected on the wafer for a series of wafers or lots exiting a process or a sequence of processes. If random (unconnected) events are the only anomalies on the wafer then the trend chart will faithfully reveal the onset of process excursions or provide useful predictions for preventive maintenance. More typically though, individual defects tend to cluster in groups, or random field events will be interspersed with group events. The most basic SPC strategy will simply count total defects detected, i.e., one defect equals one event, while other strategies will apply nearest-neighbor clustering to attempt to segment connected groups from random events. Although the second scenario improves the statistics of the trend chart, it still falls short under conditions where, for example, a long piece-wise scratch is counted as multiple events.
The analysis developed for this research provides a third scenario where large piece-wise objects can be intelligently connected into single events. Figures 8 and 9 show an example developed using the SSA tool described previously. Figure 8 represents a scenario where there are in excess of one hundred defects on each of a series of wafers. From the wafer sequence shown in the trend chart, a clustered event is emerging over time which sends the chart out of control if all defects are counted as events (i.e., the solid line passing through points w6, w8, and w9 in the plot diverges greatly from wafers w1 through w5). By
spatially clustering the events, a more useful trend can be established. The dashed line sequence in Fig. 8 is much more representative of a growing random event count.

Figure 9 represents a similar situation except the event count on the wafer sequence is very low, on the order of 10 counts per wafer. This example shows much more vividly how a proper clustering analysis can improve SPC statistics for trend monitoring. While there are truly no more than approximately 3 to 20 events occurring on each wafermap in the sequence, the original gross defect count ranges wildly between 3 and 345.

The clusters that have been determined in each of these scenarios can now be analyzed to characterize other process conditions unrelated to random events, such as mechanical damage occurring during wafer handling, or particle contamination in an isopropyl alcohol dryer (streak or stain anomalies). For a properly trained and mature SSA system, the need to manually evaluate wafermap data can be reduced or eliminated, except for further training or periodic verification. Also, the sampling plan for offline, high-resolution review can be fully automated, leaving off-line evaluation and classification of high-

Fig. 8 - Event count trend for a sequence of wafers passing through a given manufacturing process step.
resolution defect images as the only repetitive manual step in the process. It should be noted that automatic defect classification for off-line, high-resolution review is a hotbed of ongoing research with near-term commercial viability. Effective spatial signature analysis coupled with automatic defect classification has a high potential to appreciably reduce the time necessary to evaluate and correct critical yield-limiting conditions in semiconductor manufacturing, and also provide a timely return on investment for research and development in this important area.

![Image showing a grid of wafer images with event counts for each wafer.](image)

**Fig. 9** - Event count trend for a different sequence of wafers passing through a given manufacturing process.
CONCLUSION

Spatial signature analysis of electronic wafermap data has been shown to be of benefit for diagnosing and efficiently correcting yield limiting conditions which arise in semiconductor manufacturing. To ensure that the U.S. semiconductor industry maintains its globally competitive position, incremental enhancements to yield improvement strategies must continue to be developed and applied. This ongoing research has applications to automated SPC, automated signature analysis and classification, and intelligent sub-sampling for off-line, high-resolution defect review. It is anticipated that integration of this technology with in-line defect detection and analysis strategies will result in a higher rate of yield learning and ultimately yield improvement.

REFERENCES


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