CONF-9706148--1

An Integrated Spatial Signature Analysis and Automatic Defect Classification System

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Prepared by OAK RIDGE NATIONAL LABORATORY, Oak Ridge, Tennessee 37831-6285, managed by LOCKHEED MARTIN ENERGY RESEARCH CORP. for the U.S. DEPARTMENT OF ENERGY under contract DE-AC05-96OR22464.

AN INTEGRATED SPATIAL SIGNATURE ANALYSIS AND AUTOMATIC DEFECT CLASSIFICATION SYSTEM

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ABSTRACT

An integrated Spatial Signature Analysis (SSA) and automatic defect classification (ADC) system for improved automatic semiconductor wafer manufacturing characterization is presented. Both concepts of SSA and ADC methodologies are reviewed and then the benefits of an integrated system are described, namely, focused ADC and signature-level sampling. Focused ADC involves the use of SSA information on a defect signature to reduce the number of possible classes that an ADC system must consider, thus improving the ADC system performance. Signature-level sampling improved the ADC system throughput and accuracy by intelligently sampling defects within a given spatial signature for subsequent off-line, high-resolution ADC. A complete example of wafermap characterization via an integrated SSA/ADC system is presented where a wafer with 3274 defects is completely characterized by revisiting only 25 defects on an off-line ADC review station.

INTRODUCTION

This paper presents a vision of how a promising new technology called Spatial Signature Analysis (SSA) [1, 2] can improve automatic defect classification (ADC) system accuracy and throughput. Optical-based ADC technologies for semiconductor wafer manufacturing have been under heavy development for the past five years [3-10] and are just recently being seriously introduced into major semiconductor fabrication facilities [11-12]. There are many challenges in building a practical and reliable ADC system that is effective in identifying manufacturing problems in a real wafer manufacturing environment. Two closely coupled characteristics of an ADC system that are still very challenging for the system designer are (1) high defect classification accuracy and (2) high wafer throughput. Accuracy can be a problem because there can be many different classes of defects that a fabrication engineer may wish to automatically identify. To compound the accuracy problem, defects that should be grouped into the same category may have very different visual characteristics. The second challenge, throughput, is an issue because automatically classifying a defect off-line requires the defect to be repositioned under a high resolution microscope (e.g. optical or scanning electron), re-imaged, re-detected, analyzed to determine defect characteristics, and, finally, classified. This is already a time-consuming process compared to the speed at which the in-line wafer inspection is accomplished. As wafer critical dimensions shrink towards 0.18μm, optical microscopes will be replaced by slower, higher resolution SEMs for small defect review [13]. This will add more time to the defect imaging step of the process.

AUTOMATIC DEFECT CLASSIFICATION

ADC as applied in the semiconductor industry is the process of automatically categorizing wafer defects into one of multiple classes using data captured by wafer analysis instruments. The type of data that is used by the ADC algorithms varies with the application, but may be optical microscope image data, scanning electron microscope (SEM) image data, material composition information (e.g. from SEM energy

1.Managed by Lockheed Martin Energy Research Corp. for the U.S. Department of Energy under contract DE-AC05-96OR22464

dispersive spectroscopy), and confocal microscope image data, for example. There are typically three steps to the ADC process as shown below in Figure 1. Most ADC systems use reference-based image analysis, so they start with an image pair consisting of a defect image as well as a defect-free reference image. This defect-reference pair is subjected to a segmentation algorithm that localizes the defect and generates a defect mask that identifies the location and extent of the defect. This mask and the original defect-reference image pair are used to extract features, or descriptors, that uniquely describe the appearance of the defect. These features are then passed on to a defect classification algorithm that attempts to automatically categorize the new defect based on training exemplars provided by the expert human classifier.

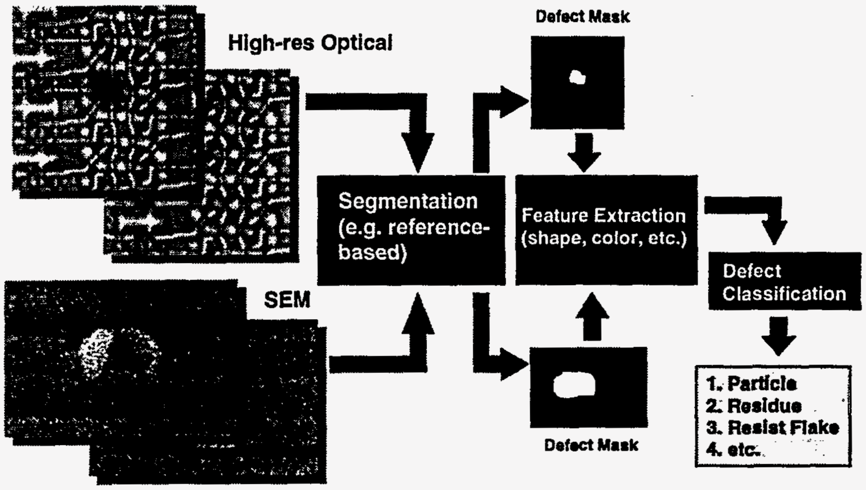

Figure 1. Typical approach for automatic defect classification of semiconductor defects. This example shows application to both optical and SEM image data

SPATIAL SIGNATURE ANALYSIS

SSA is a defect analysis technology that takes as its input a wafermap (a list of defect coordinate locations generated by an optical- or laser-based wafer inspection tool) and locates patterns of defects, or spatial signatures. SSA then classifies those signatures into a specific manufacturing problem category such as mechanical scratch, chemical vapor deposition (CVD) contamination, or spin-on-glass (SOG) streak. Figure 2 shows an example of a wafermap with multiple defect signatures that can be characterized into process specific categories. The categories that SSA will use for signature classification are user-definable and can therefore be specific to a particular manufacturer's fabrication tools. A combination of image processing, fuzzy clustering, feature extraction, and fuzzy-based classification are employed by SSA to segment and then identify the spatial signatures within the wafermap.

The resulting spatial signatures and their classifications can then be used in several different ways. First, the spatial signature may be indicative of one particular problem in the manufacturing line. For example, a particular robotic handler may leave a distinctive scratch on the wafer, and SSA may be used to automatically catch that distinctive scratch "signature" indicating that the handler must be serviced. Fast sourcing of defects is a primary goal of the SSA technology. Another potential use of the SSA results is to provide a means of intelligently sampling a subset of defects on the wafer for off-line, high-resolution review and classification. This classification step may be manual or automatic. Typically, an ADC system will use a defect wafermap to determine which of the detected defects should be revisited, imaged at high resolution, and subsequently classified. Simple clustering techniques are sometimes applied to the wafermap to separate the defects into clustered versus non-clustered groups. One cluster may then be statistically sampled to determine which of the defects will be re-imaged and classified. SSA goes far beyond simple clustering and can in many cases lead to complete manufacturing process characterization without ever performing off-line ADC on an individual defect.

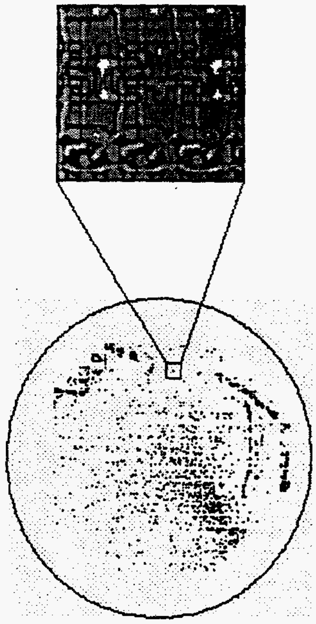

Figure 2. Defect wafermap (bottom) showing three spatial signatures: mechanical scratch (upper-left), double-slot (right), and particle contamination (lower-left). High-resolution image of particle defect (top).

SSA/ADC INTEGRATION

The integration of SSA with existing ADC technology can result in a powerful system that quickly improves yield through manufacturing process characterization. It is clear that SSA can improve the throughput of an ADC system by reducing the number of defects that must be automatically classified. For example, the large number of defects that comprise a mechanical scratch signature that is completely characterized by SSA will not need to be further analyzed by an ADC system. Even if a detected signature cannot be completely characterized, intelligent *signature-level defect sampling* techniques can dramatically reduce the number of defects that need to be sent to an ADC system. This concept is illustrated in Figure 3 where the defects within two spatial signatures are sub-sampled and classified. The bar plot in Figure 3 shows a typical result where the defects within one signature belong to one or two dominant classes. Note that a few defects fall into other, non-dominant classes, but the signature can likely be characterized for manufacturing purposes by the dominant class characteristics.

The accuracy of an ADC system can also be improved by using the output of the SSA wafermap analysis to perform *focused ADC*. Focused ADC is a strategy by which the SSA results are used to reduce the number of possible classes that a subsequent ADC system would have to consider for a given defect. For example, the SSA identification of the CVD particle contamination signature in Figure 2 can be used to eliminate many categories of defects such as missing pattern, resist flake, or corrosion. Only defect categories involving particles (dust, aluminum, organic, etc.) might need to be considered. The focused ADC concept is illustrated in Figure 4. Spatial signature analysis results (left) are used to influence the scope of classes that will be considered by an ADC system. Note that if a particular set of defects has been grouped and labeled as signature type S_A, then the entire set of possible classes, C, is reduced to those classes that fall within the S_A class subset. This pre-filtering of classes reduces the possible alternatives for the ADC system and, hence, improves that chances that the ADC system will select the correct classification. This will result in improved overall ADC performance.

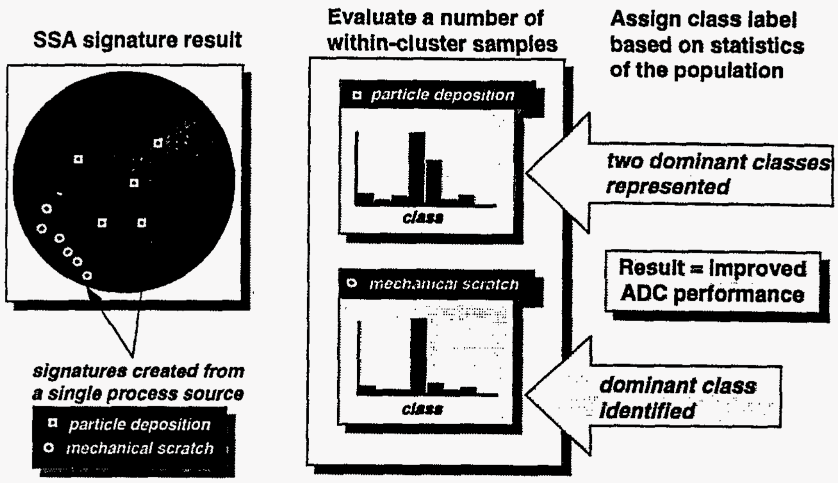

Figure 3. Illustration of signature-level defect sampling concept that allows faster, more accurate process characterization by taking advantage of the statistical similarity of defects that come from the same source (all contained in one spatial signature).

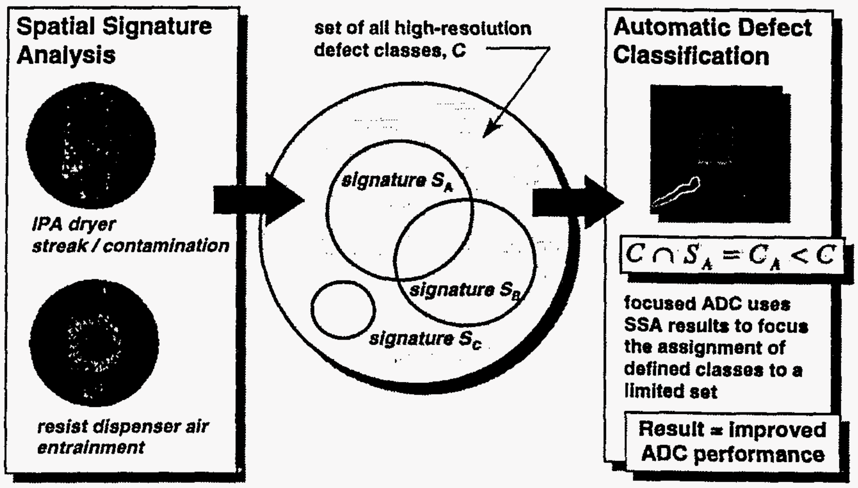

Figure 4. Illustration of focused ADC concept that uses spatial signature information to limit the scope of possible ADC classes for a defect.

SSA/ADC PROCESSING EXAMPLE

The two concepts of signature-level sampling and focused ADC are probably best described through an example of the SSA/ADC process on a wafermap that contains spatial signatures. Consider the test wafermap shown on the left in Figure 5. This wafermap contains over 3200 defects indicating some very serious problems in the manufacturing process. Typically, a substantial number of these defects would have to be reviewed by an off-line ADC system to determine the cause and/or source of the defects. This hypothetical example will show how it is possible with an integrated SSA/ADC system to characterize the entire set of 3274 defects by reviewing only 25 defects on an off-line ADC system.

The first step is to subject the test wafermap to the SSA procedure. This results in the identification of three spatial signatures: (1) double-slot, (2) CVD contamination, and (3) mechanical scratch. The double-slot signature is caused by a robotic handler that is attempting to place a wafer within a slot in a wafer boat that is already occupied by another wafer. Knowing this information about the spatial signature completely characterizes the manufacturing process for this particular problem. There is no need to revisit any of the defects within the double-slot signature for off-line review and ADC. The mechanical scratch signature is caused by a robotic handler that is scratching the surface of the wafer. Similar to the double-slot signature, the mechnaical scratch signature does not need to be further analyzed to determine the problem source. The process engineer can immediately proceed to the wafer fabrication facility to inspect and repair the problematic wafer handler. The CVD contamination signature information can be used to potentially isolate the particular CVD equipment that is contaminated, but this does not provide the process engineer with the information about the composition and source of the contaminant particles. Out of the three spatial signatures, only the contamination signature must be further analyzed to fully characterize the manufacturing problem.

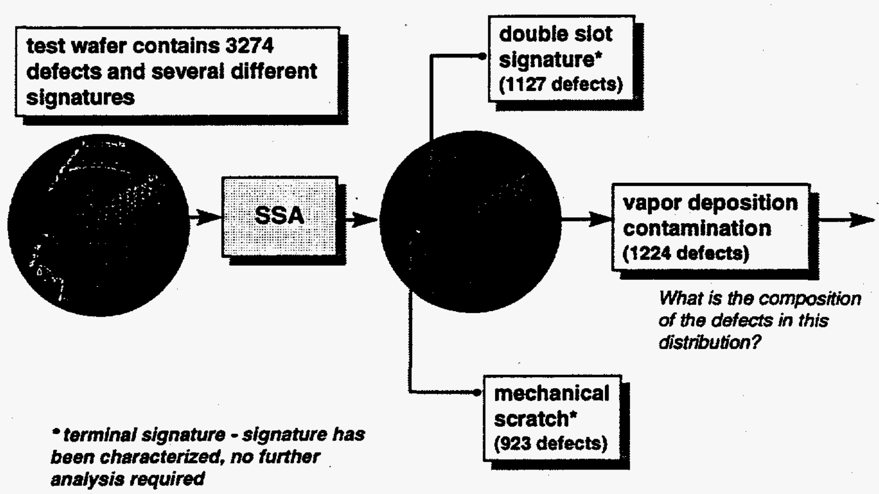

Figure 5. Sample wafermap (left) processed by SSA results in three separate signatures: (1) double-slot, (2) chemical vapor deposition contamination, and (3) mechanical scratch. Only the contamination signature must be further analyzed to determine the manufacturing problem source.

The wafermap on the left in Figure 6 (a continuation of Figure 5) contains only the CVD contamination signature. This signature can be used along with the focused ADC concept described previously to limit the number of possible ADC classes that have been historically correlated with CVD problems. In this example the entire set of N possible classes has been focused down to only three possibilities: (1) organic particle, (2) dust particle, and (3) class n (i.e. some other particle type). These three classes then become the candidate selections for the subsequent ADC process. The next step is to perform signature-level sampling and ADC by revisiting some small percentage of the total number of defects in the vapor deposition signature. In this example it is reasonable to assume that 2% (approximately 25) of the defects need to be characterized by a high-resolution ADC system to determine the composition and source of the particle within the signature. This completely characterizes the entire distribution of 3274 defects on the wafermap using an integrated SSA/ADC approach.

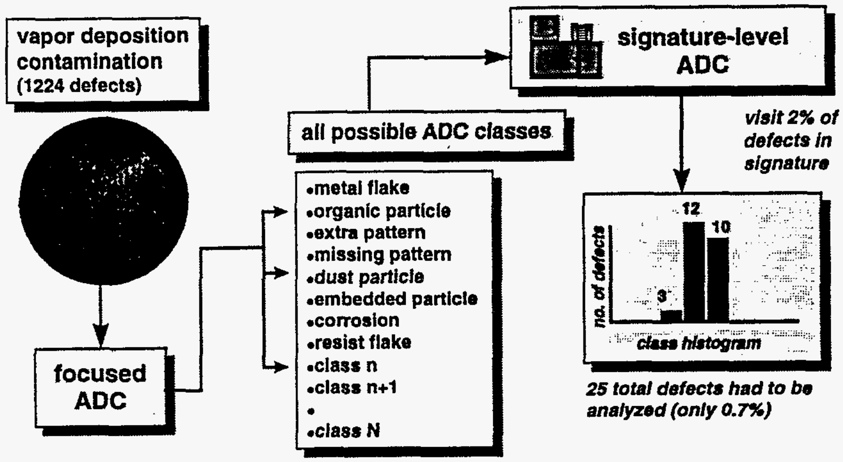

Figure 6. The vapor deposition contamination signature classification is used to focus the ADC system onto a limited number of classes, 3, out of the total possible N ADC classes (e.g. organic particle, dust particle, and class n).

FUTURE WORK

Many sensors on the semiconductor manufacturing floor collect valuable data about the state of the manufacturing process. These data sources include optical inspection microscopes, laser scattering inspection systems, electrical test probers, SEM microscopes, and in-situ particle monitors, just to name a few. As shown in Figure 7, these data sources can be grouped into spatial and temporal defect information sources.

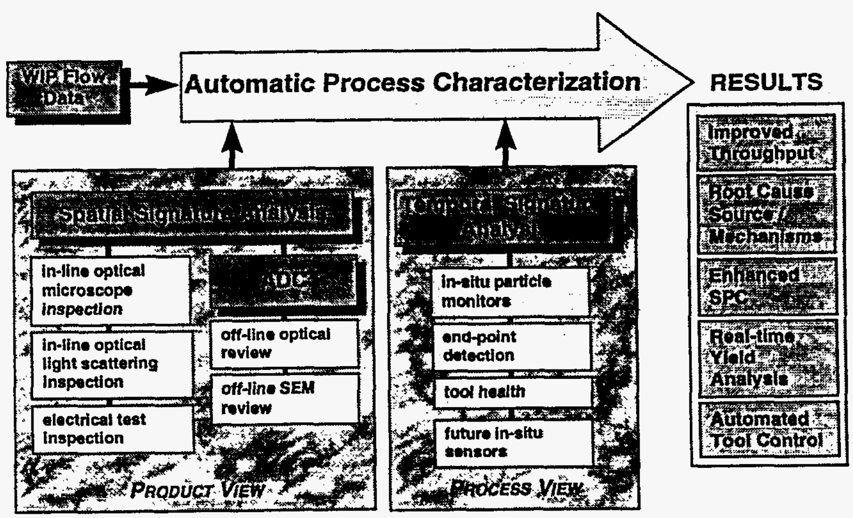

Figure 7. Multiple data sources are shown that can be used for automatic manufacturing process characterization using spatial signature analysis combined with temporal signature analysis methods.

The data streams from each of these sensors provide limited information on their own, but the combination of many of these sources contains much valuable information about the state of the manufacturing process. There are, however, no automatic process characterization (APC) tools available that can assimilate and then collectively analyze the data. In our future work, we intend to develop analysis procedures for more of these data sources (starting with electrical test and ISPM) and then attempt to fuse multiple sources with the goal of a more complete automatic process characterization. It is our belief that this can enhance many aspects of semiconductor manufacturing including throughput, root cause determination, statistical process control (SPC), and real-time yield prediction and analysis. The long-term view of such a system would be the movement towards a completely automated manufacturing fabrication facility where the APC system provides closed loop tool control.

SUMMARY

This paper provides the conceptual framework for an integrated SSA/ADC analysis system. Concepts (focused ADC and signature-level sampling) were presented illustrating how SSA and ADC algorithms and hardware can work together in an automated process characterization system for improved accuracy and throughput. A comprehensive example was presented that showed step-by-step how an integrated SSA/ADC system can quickly and accurately characterize a problematic manufacturing process. Finally, a vision of automatic process characterization was presented that will fuse data from multiple sensor inputs to provide more accurate and timely diagnosis of manufacturing problems.

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