

another illustrative embodiment, the method includes generating a second ensemble learning classifier with the identified selected number of attributes having the largest mean decrease in accuracy index. In another illustrative embodiment, the method includes determining a training error associated with the second generated ensemble learning classifier. In another illustrative embodiment, the method includes calculating a defect type pair score associated with the first defect type and the second defect type based on the determined training error.

[0009] A method for determining the sufficiency of defect data for classification is disclosed. In one illustrative embodiment, the method includes acquiring a set of defect data from a specimen, the defect data including imagery data associated with a plurality of defects including a plurality of defect types. In another illustrative embodiment, the method includes receiving a signal from a user interface device indicative of a manual classification of the plurality of defects. In another illustrative embodiment, the method includes distributing defect data of at least the first defect type into N groups of data. In another illustrative embodiment, the method includes identifying a group of the N groups of data as containing test data. In another illustrative embodiment, the method includes identifying N-1 groups of data of the distributed defect data not identified as containing test data as containing training data. In another illustrative embodiment, the method includes, for at least a first group of the N groups, incrementally generating a series of classifiers based on the training defect data contained in the N-1 groups of data, wherein each classifier is generated with an incremented percentage of at least a first defect type contained within the training defect data of the N-1 groups of data. In another illustrative embodiment, the method includes determining an accuracy value for each of the series of classifiers for at least the first defect type by applying each of the series of classifiers to the test data not contained in the N-1 groups of the distributed defect data. In another illustrative embodiment, the method includes generating a defect data sufficiency score, for at least the first defect type, based on a generated accuracy score for at least the first group of N groups and at least one additional generated accuracy score for at least one additional group of the N groups.

configured to execute a set of program instructions stored in memory. In another illustrative embodiment, the set of program instructions are configured to cause the one or more processors to: receive the one or more images from the inspection tool, the one or more images including a plurality of defect types, the plurality of defect types including a first defect type and at least a second defect type; generate a first ensemble learning classifier for the first defect type and the at least a second defect type; calculate, with the first ensemble learning classifier, a mean decrease in an accuracy index for each of a plurality of attributes associated with the first defect type and the at least a second defect type; identify a selected number of attributes having the largest mean decrease in accuracy index; generate a second ensemble learning classifier with the identified selected number of attributes having the largest mean decrease in accuracy index; determine a training error associated with the second generated ensemble learning classifier; and calculate a defect type pair score associated with the first defect type and the second defect type based on the determined training error.

[0012] An apparatus for determining sufficiency of defect data for classification is disclosed. In one illustrative embodiment, the apparatus includes an inspection tool. In another illustrative embodiment, the inspection tool includes one or more detectors configured to acquire one or more images of at least a portion of a specimen. In another illustrative embodiment, the apparatus includes a user interface device. In another illustrative embodiment, the apparatus includes a controller. In another illustrative embodiment, the controller include one or more processors communicatively coupled to the one or more detectors of the inspection tool, wherein the one or more processors are configured to execute a set of program instructions stored in memory. In another illustrative embodiment, the set of program instructions are configured to cause the one or more processors to: receive the set of defect data from a specimen, the defect data including imagery data associated with a plurality of defects including a plurality of defect types; and generate a defect data sufficiency score, for at least a first defect type, based on a generated accuracy score for at least a first group of N groups of the defect data and at least one additional generated accuracy score for at least one additional group of the N groups of defect data.

For example, the inspection tool 102 may be, but is not required to be, configured for darkfield inspection. By way of another example, the inspection tool 102 may be, but is not required to be, configured for brightfield inspection.

[0020] In one embodiment, the inspection tool 102 includes one or more light sources (not shown) to illuminate the specimen 112. The light source may include any light source known in the art. For example, the light source may include a narrow band light source, such as a laser source. By way of another example, the light source may include a broad band light source, such as a discharge lamp or a laser-sustained plasma (LSP) light source. In another embodiment, the light source may be configured to direct light to the surface of the specimen 112 (via various optical components) disposed on the sample stage 115. Further, the various optical components of the inspection tool 102 are configured to direct light reflected, scattered, and/or diffracted from the surface of the wafer 112 to a detector (not shown) of the inspection tool 102. The detector may include any appropriate light detector known in the art. In one embodiment, the detector may include, but is not limited to, a charge coupled device (CCD) detector, a photomultiplier tube (PMT) detector, and the like.

[0021] It is noted that for purposes of simplicity the inspection tool 102 has been depicted in a simplified block diagram. This depiction, including the components and geometrical configuration, is not limiting and is provided for illustrative purposes only. It is recognized herein that the inspection tool 102 may include any number of optical elements (e.g., lenses, mirrors, filters, beam splitter and the like), energy sources (e.g., light source or electron source) and detectors (e.g., light detector or secondary electron detector) to carry out the inspection of one or more portions of wafer 112 disposed on the sample stage 115.

[0022] In another embodiment, the system 100 includes a controller 104. In one embodiment, the controller 104 is communicatively coupled to the inspection tool 102. For example, the controller 104 may be coupled to the output of detector 103 of the inspection tool 102. The controller 104 may be coupled to the detector in any suitable

to, image feature amounts, defect coordinates, composition analysis results, manufacture initiation history data, or machine QC (Quality Control) data. Further, in some embodiments, the one or more attributes may be obtained from multiple types of defect inspection tools or systems, such as, but not limited to, an optical or SEM foreign matter inspection machine, a pattern inspection machine, a defect review machine, SPM, or an elemental analysis machine. Attributes suitable for classification of defects is described in U.S. Patent No. 7,602,962, issued on October 13, 2009, which is incorporated herein by reference in the entirety.

[0037] In one embodiment, the attributes of the one or more training defects may be processed by an automatic classification function, such as, but not limited to, a real time automatic classification (RT-ADC) to classify one or more training defects. It is noted that the utilization of RT-ADC provides for a “rough” automatic classification of training defects without sacrificing high processing speeds. Real time automatic classification is described generally in U.S. Patent No. 7,602,962, issued on October 13, 2009, which is incorporated above by reference in the entirety.

[0038] In step 206, an ensemble learning classifier is generated. In one embodiment, the ensemble learning classifier is generated, or trained, based on the manual classification of training defects of step 204 and the one or more attributes. In one embodiment, the one or more processors 106 of controller 104 may generate, or train, the ensemble learning classifier and store the ensemble learning classifier in memory 108. In one embodiment, the ensemble learning classifier is a random forest classifier. The one or more processors 106 may train a random forest classifier that operates by constructing multiple decision trees during a training period and outputting a class that is the mode of the classes of the individual trees. In this regard, the one or more processors 106 may use the manual classification of the training defects and the associated attributes to train a random forest classifier. The implementation of a random forest classifier is described generally by Breiman in *Random Forests*, Machine Learning, Vol. 45, Issue 1, pp. 5-32 (2001), which is incorporated herein by reference in the entirety. Random forests are also discussed by Kulkarni et al. in *Random Forest Classifiers: A Survey and Future Research Directions*, International Journal of

Advanced Computing, Vol. 36, Issue 1, pp. 1144-1153 (2013), which is incorporated herein by reference in the entirety.

[0039] In another embodiment, the ensemble learning classifier is a support vector machine (SVM). The one or more processors 106 may use the manual classification of the training defects and the associated attributes to train a SVM-based classifier. The implementation of a SVM-based classifier is described generally by Xie et al. in *Detection and Classification of Defect Patterns in Optical Inspection Using Support Vector Machines*, Intelligent Computing Theories Lecture Notes in Computer Science, Vol. 7995, pp. 376-384 (2013), which is incorporated herein by reference in the entirety.

[0040] In step 208, a confidence threshold for each defect type of the one or more training defects is generated. In one embodiment, the one or more processors 106 generate a confidence threshold for each defect type of the one or more training defects based on a confidence threshold received from user interface 110. In another embodiment, the confidence threshold is generated by one or more processors 106 via a cross-validation procedure. In another embodiment, the confidence threshold may be manually set via user input (e.g., user input via user interface 110).

[0041] For example, a user may select a purity requirement, or purity level, via user interface 110. In turn, the user interface device 110 may transmit a signal indicative of the selected purity requirement to the one or more processors 106 of controller 104. The controller 104 may then store the selected purity requirement in memory 108. It is noted herein that the received purity requirement may be a function of a variety of parameters. For instance, the received purity requirement may depend on a user preference and/or the expected defect types present on a given production wafer. For instance, a user may select a single classification purity requirement (e.g., 90%) on all defect types. In another instance, a user may select a first classification purity requirement (e.g., 90%) on a first defect type and a second classification purity requirement (e.g., 85%) on a second defect type and so on. It is further noted that in some embodiments a heightened purity requirement correlates to a higher confidence

threshold. In this regard, the one or more processors 106 of controller 104 automatically adjust the confidence threshold in response to a user input via user interface 110.

[0042] In step 210, one or more images including one or more test defects are acquired. In one embodiment, the one or more test defects are disposed on a different specimen (e.g., wafer) than the one or more training defects. For example, the inspection tool 102 may acquire imagery data from a production specimen (e.g., wafer), whereby the controller 104 extracts one or more test defects from the given imagery data. Further, the training defects, used to generate the ensemble learning classifier, may be extracted from imagery data from a training specimen. In another embodiment, the one or more test defects and the one or more training defects of the present disclosure are disposed on the same specimen (e.g., wafer). In this regard, the imagery data (e.g., one or more images) used to extract the training defects is also used to acquire the one or more test defects of the present disclosure.

[0043] In step 212, the one or more test defects are classified with the generated ensemble learning classifier. In one embodiment, the one or more processors 106 may retrieve the ensemble learning classifier stored in memory 108 (see step 206) and apply the ensemble learning classifier to one or more test defects acquired in step 210. In this regard, once the ensemble learning classifier has been trained in step 206 it may then be used to classify one or more test defects contained in imagery data acquired from a given sample (e.g., production wafer).

[0044] In step 214, a classification confidence level is calculated for each of the one or more test defects. In one embodiment, the one or more processors 106 calculates a confidence level for each, or at least some, of the one or more test defects with the ensemble learning classifier trained in step 206. It is noted herein that the confidence level of the classification for the one or more defects may be calculated in any manner known in the art. In one embodiment, the one or more processors 106 calculate the confidence level of the one or more test defects via a voting procedure. For example, in the case of a random forest classifier, each tree of the random forest classifier has a

all or in part by the system 100. It is further recognized, however, that the method 400 is not limited to the system 100 in that additional or alternative system-level embodiments may carry out all or part of the steps of method 400. It is further noted that the embodiments and examples described in the context of methods 200 and 300 should be interpreted to extend to method 400 (and vice versa) unless otherwise noted.

[0062] In step 402, one or more images 107 are acquired including multiple defect types. In one embodiment, the inspection tool 102 acquires one or more images 107 and transmits the one or more images 107 to the one or more controllers 104.

[0063] In step 404, a manual classification of the one or more defect data is carried out. For example, a user may manually classify the defects of the defect data contained in the one or more images 107. For instance, a user may manually classify the defects via user interface device 110 based on one or more attributes of the one or more defects. In turn, the user interface device 110 may transmit a signal indicative of the manual classification of the one or more defects of the specimen 112 to the one or more processors 106 of controller 104. In another embodiment, the controller 104 may receive the manual classification of the defects and store the result in memory 108. The one or more attributes used to carry out the classification of step 404 include any one or more attributes that can be derived from a defect inspection or review tool. For example, the one or more attributes may include, but are not limited to, image feature amounts, defect coordinates, composition analysis results, manufacture initiation history data, machine QC (Quality Control) data. Further, in some embodiments, the one or more attributes may be obtained from multiple types of defect inspection tools or systems, such as, but not limited to, an optical or SEM foreign matter inspection machine, a pattern inspection machine, a defect review machine, SPM, or an elemental analysis machine. Attributes suitable for classification of defects is described in U.S. Patent No. 7,602,962, issued on October 13, 2009, which is incorporated previously herein by reference in the entirety.

[0064] In one embodiment, the attributes of the one or more training defects may be processed by an automatic classification function, such as, but not limited to, a real time