Speeding Populated Board Inspection: A New Technology

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Abstract

The need for automated populated board inspection stems from the desire to reduce the number of defective board escapes, and to improve the yield of the production line. There are two main goals of populated board inspection: 1) to detect and classify defects, 2) provide process control information. Although at first glance the goals may appear to be independent, they are actually very closely related through the technology used to perform populated board inspection. The current generation of inspection technology typically trades classification accuracy - and hence the ability to provide meaningful process control information - with detection ability and ease of implementation. So while the current generation of technologies may be able to *detect* a wide range of anomalies on the populated board, ***detection is not the same as classification.*** Detection without robust classification will not lead to improved production yields because the information needed to improve the process will not be collected.

In this paper we briefly overview the current generation of inspection technology, presenting its weaknesses with respect to the two stated goals. In order to address these goals, a new approach to populated board inspection is described.

Goals of Populated Board Inspection

There are two main goals of populated board inspection. The first is to detect and classify a wide range of visually detectable defects. The complete range of defects is typically specified by the IPC level two specification [1]. Some of these defects are at the component level, such as missing, off-pad, reverse-polarity, wrong component, and foreign material. Other defects at the lead level include bent and missing leads, individual lead skew, and solder bridges. Finally, at the lead level, defects include visual inspection of solder joints for dewets or insufficient solder. The second goal is to do the detection and classification in such as way as to produce process control information that can be used to improve production yields by reducing the number of defective boards produced, and by reducing the time those defective boards are in rework. We first discuss the current generation automated visual inspection technology, its strengths and weaknesses in light of the two above-mentioned goals.

Current Technology

The current generation technology has been based on a technology called *templating*[2]. A template is an image of a component or section of populated board that is assumed to be good. As new boards are being inspected, the template is subtracted from the image of the same component or board section taken from the board under inspection. The template is divided into a number of different regions, each with one or more threshold values that are used to determine if there is a defect in that region or not. The magnitude of the difference between the image under inspection and the template is compared to the threshold, and a decision is made (see Fig.1).

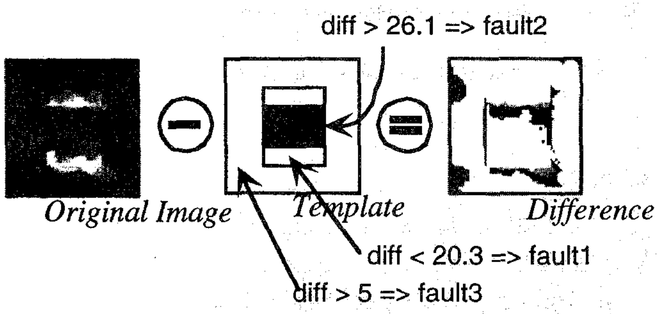

Fig. 1. Templating technology. Templating technology uses an idealized version of the original image to difference with a captured image, along with threshold value limits to determine where a defect might occur.

Templating as a technology for automated visual inspection of populated boards has some benefits that in the past have made it a viable approach. The principal benefits of this approach are that it is conceptually very simple and straightforward to implement in hardware. The ease of implementation has led to the development of specialized hardware designed to process a single image frame very quickly. The method is also capable of *detecting* many possible errors, and when defect sizes are relatively large, there is enough flexibility in the specification of the "important" regions around a component that classification of the detected defects are also possible.

With these benefits, there come drawbacks as well. While templating technology is conceptually simple to understand and implement, it is very difficult to extend. As new defects arise, functional additions must be made to the templating decision method (i.e., the magnitude of the differences triggers computational functions to be run, and the defect decision is made on the output of the function.) Prior hardware implementations made on the basis of a camera size and resolution capable of handling larger defects size may now pose a problem as higher resolutions are needed to distinguish current defects.

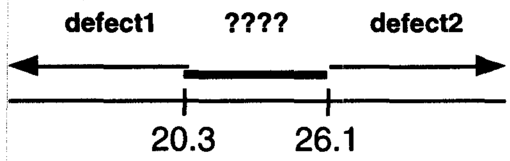

Fig. 2. Templating Decision Procedure. In order to make a classification decision, the thresholds associated with a template are used to segment the decision space into regions associated with the occurrence of defects.

However, the very feature of the technology that has made it effective at automated visual inspection of populated boards in the past - that it is capable of *detecting* discrepancies between the board under inspection and a template - is the aspect that is making it inapplicable to today's inspection problem. We'll take time here to elaborate a little more on this.

Fig. 2. graphically represents the templating decision procedure, the method by which a templating inspection machine makes classification decisions. Since the magnitude of the difference is the only data representation used, the decision space can be depicted as a number line. Two thresholds, or decision boundary points, are shown in the figure. If the magnitude of the difference is below 20.3, then the image is said to contain defect1. If the magnitude of the difference of images is greater than 26.1, then the image is said to contain defect2. The area between 20.3 and 26.1 is either undetermined, or is set by the machine programmer to be ignored.

The programmer of the inspection station has the ability to set thresholds in such a way that any image that is not *exactly* the same as the template will be flagged as a defect. With this overly strict criteria in effect, there is no possibility of having an escape (assuming that the template is indeed perfect.) However, the templating system will now falsely fail a very large number of components for very minor discrepancies. With such minor differences between board under inspection and template, the ability of the system to classify the "defect" will be severely compromised. Because of this, it is common for templating systems to present all of their defect decisions to a human operator for verification. While in some circumstances it might be beneficial to perform this verification in the production line, it dramatically reduces the usefulness of the inspection equipment in the first place.

An interesting situation arises during verification when an image produces a magnitude difference that falls below the 26.1 mark - say 25.7 - but is still and instance of the class defect2. To handle this, the programmer of the templating system must reset the threshold value (26.1) to a new value that will now include 25.7. What new value should be chosen? A conservative approach would be to set the new threshold value at 25.699 so that the threshold will be moved only enough to encompass the misclassified instance. A more liberal approach would be to set it to 25.3, which is the same distance from 25.7 as 25.7 is from 26.1. There are a number of very complex procedures that have been developed to set threshold values, and most of them use a set of example defects to verify the changes made.

Templating methods work well where there is very little variation in the images to be classified. In the past, component sizes have been large enough and production rates have been slow enough that templating methods could apply threshold values creatively to produce a working solution. However, for current generation board manufacturing, there are numerous variations that will all produce satisfactory computer boards - solder shape, shadows or reflections, replacement generic parts, and minor placement differences - and yet at the very fine scale at which they are produced, the variations represent a majority of the component itself. All of these variations make it more difficult to apply templating technologies to today's populated board inspection problem.

The inability of the templating decision method to deliver high performance *classification* as well as detection has two main causes. First, the templating decision method attempts to use the same base data - magnitude of image difference - to make many different types of distinctions. This representation of the problem is simply not sufficiently complex to enable subtle distinctions to be made between similar classes. The second reason that templating methods have difficulty in translating detection into classification is that their classification decision method treats each type of defect as if it were independent of the other defect types. From the previous example, the decision to classify an image as having either defect1 or defect2 depends solely on the individual threshold values. This makes the decision to classify an image as having defect1 independent from the decision to classify an image as defect2. To make the decision dependent, some method would have to be devised that would relate the magnitude of the difference of the template and image under inspection with the threshold values that trigger the decision for defect1 and defect2. Doing this reliably with the ad hoc methodology used to choose the threshold values would result in a drastic increase in the already long template programming and setup times.

A New Technology for Visual Inspection

The weaknesses of templating techniques and other techniques that rely on the independence of defects has led IRSI to develop a new and fundamentally different technology for visual inspection. It is called Adaptive Knowledge-based Reasoning and seeks to store generic inspection knowledge in a database and use that knowledge to generate high-quality defect detection and classification. We have implemented a system based on this technology, called the Automated Inspection and Measurement Station (AIMS™).

Fig. 3. depicts the basic flow of operation in the AIMS™. The image is obtained from a camera and is then transformed into a set of symbolic and real-valued features. This transformation is accomplished through the use of the board's CAD component location information, rules for determining what set of preprocessing routines need to be run on the image, and traditional image processing routines for generating feature values. The computation and aggregation of the feature values can be viewed as a re-description of the image that was previously represented as a set of pixels, and is now represented as a set of feature-value pairs. It may not be obvious that the set of feature-value pairs - or descriptors - is an accurate description of the image in question. In fact, it generally is not. However, it need not be a complete description of the image if the set of descriptors are chosen so that they provide the information necessary to determine if a defect exists, and if it does, to what class of defects does it belong; i.e. if the descriptors reflect the semantics of inspection. Indeed, the knowledge base of the AIMS is engineered so that it has a very general, very wide breadth of knowledge about the inspection and classification of board assembly components. This knowledge is stored in such as way as to permit the historical similarity-based classification decision making methodology to be employed during decision making. This method of classification uses a knowledge base of general inspection knowledge that is the same for all board types inspected and that is augmented with specific knowledge of how defects on different components of a given board typically look.

The decision methodology is shown in Fig. 4. One way to look at the tree-like structure depicted at the far right of Fig. 3. is as a multi-dimensional space. This multi-dimensional space reflects the partitioning of knowledge into regions that correspond to either a defect class or to a prototypical defect. A similar situation arises in the AIMS decision method as in the templating decision method; that is, suppose that the new training point marked ???? (see Fig. 4) is presented for inspection, how should the system classify this point? Because it is outside of the decision boundaries for defects 1 and 2, it cannot be said with confidence that the new point is a member of either class. Contextually, the relative similarity between the new point and defect classes 1 and 2 are roughly equivalent. Looking at class information, such as the "spread" or spatial coverage of the class may allow AIMS to prefer defect class 1 over defect class 2, since class 1 is larger and more spread out than class 2. This is the preferred answer in this case, which is almost exactly half way between the two existing classes. The answer may be correct, that it is a defect of class 1, in which case the resulting decision space looks like Fig. 4a. Whether correct or not, in cases where a high confidence answer cannot be made, the user is solicited for an opinion. The information gained from the user can create decision spaces such as Fig. 4b, where the point is a member of defect class 2, or Fig. 4c, where it is a member of a new defect class. The important thing to note is that the determination of the defect class is made by taking into account the relative similarity between the new point and defect classes 1 and 2.

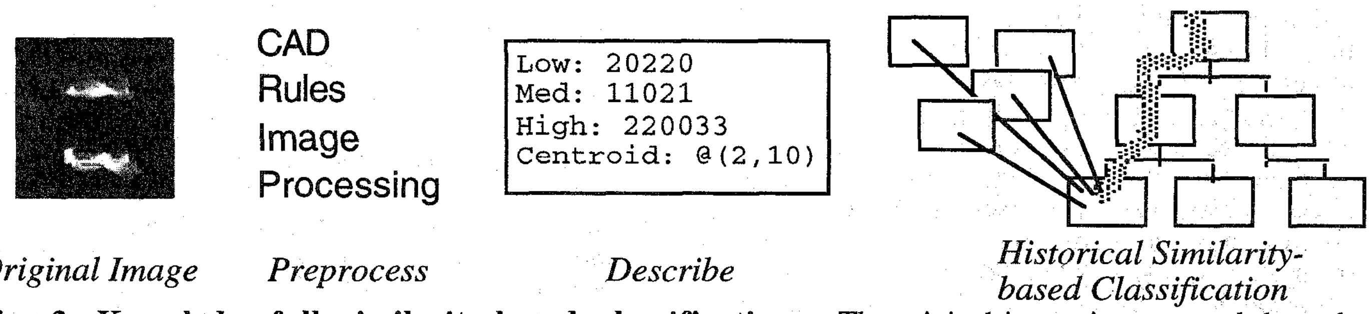

Fig. 3. Knowledge-full similarity-based classification. The original image is converted through the use of CAD, rules, and traditional image processing techniques to produce a set of features that describe the object in the image. The particular descriptors used complement built-in knowledge of classification and inspection in general.

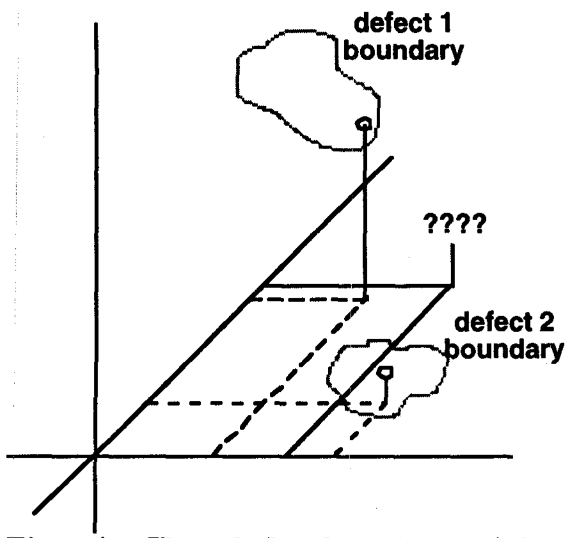

Fig. 4. Knowledge-based decision method. Compared to the templating approach, the knowledge-based classification approach has much greater freedom to make distinctions between those variations that are acceptable, and those that indicate a defect.

Our approach has a number of advantages over traditional approaches to machine vision and inspection:

1. Images are represented in semantic space. Rather than work directly with image pixels (syntactic space) or with simple geometric descriptions of images (symbolic space), the AIMS system represents information contained in the image with semantically meaningful descriptions (semantic space). The descriptions are semantically meaningful because they embody the most descriptive components of the image with respect to the ability to distinguish a defect class or set of classes from others.

2. Defects can be arbitrarily close. In thresholding systems, one of the difficult things to resolve is two defect classes that are visually quite similar. The AIMS systems allows defect classes to be arbitrarily close to one another as long as there is at least one feature with which they can be discriminated. This capability precludes the use of static thresholds and difference-distance calculations.

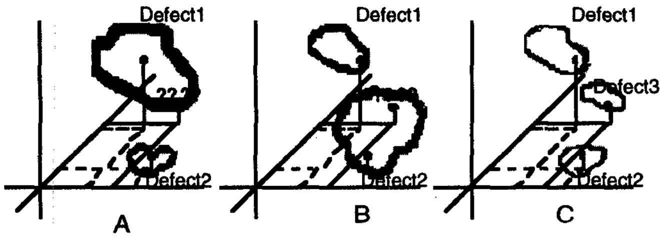

Fig. 5. Possible classification outcomes. The results of AIMS classification will modify the decision space.

3. New information on defect classification can be introduced at any time. New knowledge on defect classification can be introduced at any time during AIMS system operation. As shown in Fig. 4, and new data point can be added that corrects a falsely held assumption about the boundary between two defect classes. And because of item 2, we know that the addition of this new knowledge can be used to refine the decision boundary between the two classes to an arbitrarily fine degree.

4. Knowledge introduction is additive. With respect to the class being modified by the introduction of new information (item 3), the AIMS knowledge base will not reclassify any other member of an existing defect class. Unlike templating methods, where the modification of a threshold value might upset the classification accuracy of a number of defect classes.

5. Decision making is explainable, justifiable, and correctable. The decision making component of the AIMS has a built-in explanation and justification procedure that enables any classification made by the system to be presented to the user in an easy to understand fashion. Many times the explanation is based on previous interactions with the user, enabling the growth of trust in the operation of the system.

6. Speed increases are dramatic and sustainable. Because the technology behind the AIMS system is designed in a object-oriented, modular fashion, the speed at which the system runs can be easily modulated by the type of computational support given to it. This feature allows inspection times in the range of 45 seconds to below 20 seconds for a typical 20"x18" motherboard.

Impact of the New Technology

This new technology for populated board inspection has potential - unlike any inspection systems seen before it - to fill in many of the information gathering holes in current assembly production processes.

1. Detect and Classify relevant defects. AIMS technology, like no other system before it, has the ability to make informed, reasoned judgments on the components in those images. AIMS can do this because it works with semantic descriptions of images that are designed to maximize discrimination between defect classes, and because it has the knowledge to make those decisions with regard to other possible defects.

2. Provide accurate process control information. The ability to provide accurate defect classification information is the key requirement for providing accurate process control information. Detection of anomalies is not enough to generate useful process control information because the resulting data will

not be timely and consistently accurate because it is relying on human operators to make classification decisions. Because AIMS classifies anomalies as either a defect requiring rework, or simply an acceptable variation of a component, both the defects and the variations can be tracked.

3. Reduce false alarms. The ability to accept new information from the user in real-time allows the system to reduce the number of false alarms that it produces, and eliminates the reoccurrence of any particular false alarm. As was discussed in items 2, 3, and 4 in the previous section, the knowledge structuring and decision making features of AIMS allows it to learn the correct classification of a defect that was classified incorrectly and never repeat that error again. The corrected classification becomes part of the knowledge base that is retained from run to run, applying the learned knowledge to a wide variety of new component instances.

4. Simplify programming of new boards for assembly. One pragmatic aspect of populated board inspection that is made significantly easier by the adaptive learning technology employed by AIMS is the time required to bring a never-before-seen board through inspection. "Programming" AIMS is done by presentation of a sample board (populated and unpopulated) and through point-and-click selection of inspection criteria preferences.

5. 100% inspection. The speed of AIMS gives the contract or OEM board manufacturer the ability to perform 100% inspection of boards assembled on an AIMS equipped production line. This can be viewed in two ways: 1) it provides a gate facility that prevents defective boards from escaping the manufacturing facility; and 2) it provides continuous monitoring feedback that allows new insights into the production process to be found and exploited.

Conclusions

In this paper we have discussed the two main goals of populated board inspection systems - to detect **and classify** relevant defects, and to use that information to provide high-quality and timely process control data to production line managers. We presented an overview of the current state-of-the-art inspection station technology and showed why it lacks the characteristics necessary to perform reliable classification of the typically high-variation component samples found on populated boards. We then turned to a new technology - adaptive knowledge-based reasoning - developed specifically to address the complicated information processing requirements of the board inspection task.

In doing this we have come to some basic conclusions that pose significant hurdles for current generation inspection stations. The first conclusion is "*Detection is not classification.*" It is no longer adequate for machine vision systems to simply detect anomalies on the populated board - there are simply too many of them that are perfectly viable component constructions. To be effective in supplying manufacturing engineers the information they need to improve yields on the production line, inspection stations must provide accurate classification (both defective and non-defective) of the anomalies and report defects and variations to the user in a way that allows predictions of production line performance to be inferred.

A second conclusion is that *simple decision methods produce inadequate decisions in the populated board inspection domain.* The number of variations in properly constructed boards will defeat any decision method that treats defect classes as independent entities. This applies not only to the templating decision method, but to other methods, such as pattern recognition systems.

The final conclusion is that *the benefits of adaptive knowledge-based reasoning technologies such as found in the AIMS system go beyond accurate classification by making the setup, operation, and maintenance a simple, end-user task.* The key to this is the facility for increasing the knowledge and skill in one aspect of the inspection station knowledge base without detracting from it's other aspects. This results in more accurate classification, and more timely and high-quality data for process control.

The goal of any production line machine is to increase the efficiency and efficacy with which boards can be produced. The adaptive knowledge-based reasoning technology employed by AIMS gives the contract manufacturer or OEM the tool needed to monitor production quality and to take action to increase quality. Speeding populated board inspection requires just such a tool.

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