Image Retrieval in the Industrial Environment

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ABSTRACT

The ability to manage large image databases has been a topic of growing research over the past several years. Imagery is being generated and maintained for a large variety of applications including remote sensing, art galleries, architectural and engineering design, geographic information systems, weather forecasting, medical diagnostics, and law enforcement. Content-based image retrieval (CBIR) represents a promising and cutting-edge technology that is being developed to address these needs. To date, little work has been accomplished to apply these technologies to the manufacturing environment. Imagery collected from manufacturing processes have unique characteristics that can be used in developing a manufacturing-specific CBIR approach. For example, a product image typically has an expected structure that can be characterized in terms of its redundancy, texture, geometry, or a mixture of these. Defect objects in product imagery share a number of common traits across product types and imaging modalities as well. For example, defects tend to be contiguous, randomly textured, irregularly shaped, and they disrupt the background and the expected pattern. We will present the initial results of the development of a new capability for manufacturing-specific CBIR that addresses defect analysis, product quality control, and process understanding in the manufacturing environment. Image data from the semiconductor-manufacturing environment will be presented.

Key Words: content-based image retrieval, manufacturing environment, semiconductor yield management, hierarchical pattern recognition, similarity measures

1. INTRODUCTION

The ability to manage large image databases has been a topic of growing research over the past several years. Imagery is being generated and maintained for a large variety of applications including remote sensing, art galleries, architectural and engineering design, geographic information systems, weather forecasting, medical diagnostics, and law enforcement. Content-based image retrieval (CBIR) represents a promising and cutting-edge technology that is being developed to address these needs [1]. CBIR refers to techniques used to index and retrieve images from databases based on their pictorial content [1,2]. Pictorial content is typically defined by a set of features extracted from an image that describe the color [3,4], texture [5,6] and/or shape [7,8,9] of the entire image or of specific objects. This feature description is used in CBIR to index a database through various means such as distance-based techniques, rule-based decision making, and fuzzy inferencing [10,11,12]. The manufacturing environment represents an application area where CBIR technologies have not been extensively studied. The low cost of computer systems, memory, and storage media have resulted in manufacturers collecting and storing more information about the manufacturing process. Although this includes information about the processes themselves (e.g., to facilitate process characterization and control), much of the data being stored is product imagery collected from automated inspection tools. This imagery contains an historical record of manufacturing events that cause a reduction in product quality. In this paper we will discuss our approach and preliminary results to the application of CBIR technologies to the industrial environment.

1.1. Background

CBIR research as currently described in the literature illustrates an ongoing attempt to solve a generalized image management problem, and as such, does not yet address the solution of problems such as those found in the manufacturing environment. That is not to say that there are no developed systems available to the public and scientific communities. We have, for example, performed a basic evaluation of two such systems: the Query by Image and Video Content (QBIC) System [13] created by researchers at the IBM Almaden Research Laboratory, and the Multimedia Analysis and Retrieval System (MARS) [14] created by researchers at the University of Illinois at Urbana-Champaign. These systems allow the user

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to perform image queries based on attributes such as color, shape, and texture, and can match general similarities between test and target imagery. What these state-of-the-art systems also reveal is a difficulty in performing specific searches to extract subtle information from image databases. Based on the available literature, CBIR research has focused primarily on general architectural issues for addressing concepts as opposed to applications. In this paper we describe an initial approach that focuses CBIR technology on the particular application domain of manufacturing-specific CBIR.

1.2. The Manufacturing Environment

Images collected from manufacturing processes have unique characteristics that can be used in developing a manufacturing-specific CBIR approach. For example, a product image typically has an expected structure that can be characterized. The structure can be regular, i.e., repetitive, or it can be textured. If it is the latter, the statistics of the texture can be quantified. A product might also contain predictable geometric patterns. Some mixture of these basic structures is likely as well. The important point is that they are expected, quantifiable, and bounded for a particular application domain. Defect objects in product imagery share a number of common traits across product types and imaging modalities as well. For example, defects tend to be contiguous, randomly textured, irregularly shaped, and they disrupt the background and the expected pattern.

Figure 1 shows several examples of textile and semiconductor images captured using optical imaging, optical microscopy, and scanning electron microscopy (SEM). Although these images come from very different manufacturing processes and imaging modalities, they share the structural characteristics described above, i.e., they have consistent texture across an image type (i.e., for a given product), they have repetitive structure, or they have regular geometric shapes. The defects that are present are randomly shaped and textured and they disrupt the background pattern. These observations suggest that a CBIR approach can be developed to describe image content in terms of these image properties. This approach could produce a query system capable of extracting or collecting subtle image information regarding the image type. It would also be possible to specify a query based on one image for background and another image for defect type, e.g., to find all images of one substrate type with another defect type.

Figure 1 – Imagery collected in the textile and semiconductor manufacturing environments show structure that can be leveraged to apply manufacturing-specific CBIR technology. Clockwise from upper left: textile, semiconductor (optical), textile, textile, semiconductor (optical), textile, semiconductor (SEM), semiconductor (SEM), semiconductor (optical), and semiconductor (SEM).

1.3. Automated Inspection

Automated detection and classification systems are becoming commonplace in industrial environments. Reference [15] presents an overview of the many applications and methods being researched and implemented for automated visual inspection, including both in-house and commercial systems. The primary function of these systems is to segment and classify defects, where a defect can be defined as a region in the image that deviates from an expected pattern or specification. The most common methods for performing defect analysis are described in Table I.

Table 1 – Examples of defect detection methods in use in various industries today.

METHOD	DESCRIPTION	EXAMPLE APPLICATIONS
Threshold	A simple threshold is set to detect deviations in an expected uniform background. The process usually requires post filtering to remove small nuisance anomalies that arise due to image noise.	Continuously manufactured web products such as paper and film products; unpatterned thick- and thin-film ceramics; etc.
Golden Template	A single reference image of a non-defective product is maintained as a template for subtractive comparison followed by thresholding / filtering	Printed textiles; printed graphics; semiconductors; printed circuit boards; patterned technical ceramics (e.g., multi-layer packages), etc.
Neighborhood Template	A dynamic reference image is updated and maintained based on neighboring product. This dynamic reference image is applied in the same manner as a golden template.	Printed textiles; printed graphics; semiconductors; printed circuit boards; patterned technical ceramics; etc.
CAD Specification	A grey-scale template is derived from a CAD design specification. The is used in a similar manner to the golden template. This technique is especially useful for verifying dimensional specifications.	Printed circuit boards; flexible printed circuit product; patterned technical ceramics; multi-layer packages; etc.
Non-spatial Techniques	These are methods that measure variations in characteristics such as texture or color to locate and segment anomalous conditions. The application is to products that exhibit non-geometric but statistically expected structure.	Non-woven textiles; unpatterned woven and knit textiles; specialty paper products; etc.

Figure 2 shows a typical computer vision process for detecting a defect based on the golden template or neighborhood reference method. This technique, like all those described in Table I, result in the generation of a mask that represents a segmentation of the defect from the expected regions of the image. In CBIR this provides an additional level of description that can produce focused and specific queries. For example, the user's query can focus the search on the defect type, since this region of the image can be characterized independent of the background, or it can focus on the substrate. The substrate would contain all regions not impacted by the defect mask. This segmentation mask is an inherent component of the detection process and therefore provides an extra piece of information about the structure of the data that is not readily available in general purpose CBIR systems.

2. SEMICONDUCTOR YIELD MANAGEMENT ENVIRONMENT

Semiconductor manufacturing is representative of an industry that has a mature computer vision component for the inspection of product. Digital imagery for failure analysis is generated between process steps from optical microscopy and laser scattering systems and from confocal, SEM, atomic force microscope and focused ion beam imaging modalities. This data is maintained in a yield management database and used by fabrication engineers to diagnose and source manufacturing problems, verify human assertions regarding the state of the manufacturing process, and to train inexperienced personnel on the wide variety of failure mechanisms observed. We have been working with the semiconductor industry since 1991 and have helped establish new methodologies and procedures for automatic defect classification [16,17] and spatial signature analysis [18,19,20]. Both of these research areas are based on the analysis and automatic classification of image-based anomalies that impact device yield.

The semiconductor industry currently has no direct means of searching the yield management database using image-based queries. The ability to query the fabrication process is based primarily on date, lot, wafer identification number (ID), etc. Although this approach can be useful, it limits the user's ability to quickly locate historical information. For example, if SEM review has determined that a particular defect or pattern problem exists on a wafer, the yield engineer must query on dates, lots, wafers, etc., to find similar historical instances. Although roughly 70% of all space occupied in the database consists of imagery [21], queries to locate imagery are manual, indirect, tedious, and inefficient. Therefore, this becomes an iterative and slow process that can prove unwieldy in today's semiconductor environment where a single manufacturing

campus (i.e., multiple fabrication facilities at one site) can generate thousands of images daily. If a query method can be designed that allows the user to look for similar informational content, a faster and more focused result can be achieved. A process for locating similar imagery based on image content (i.e., the image structure as opposed to lot number, wafer ID, date, etc.) would result in a reduced time-to-source

CBIR represents just one of the many technologies and directions that will impact future yield management strategies. Coupling content-based image analysis with the informational content already being extracted by other automation tools in the semiconductor industry will provide the yield engineer with powerful search and discovery capabilities. The same assertions hold true for other manufacturing environments where product imagery is being collected and stored such as textiles, steel, paper, glass, and films manufacturing. After a discussion of our technical approach for manufacturing-specific CBIR in Section 3, we will present preliminary CBIR results based on a limited database of semiconductor images in Section 4.

Figure 2 – A typical computer vision process used to detect a defect between a test and a reference image. The result is a binary defect mask that segments the anomaly from the expected image components.

3. TECHNICAL APPROACH

Figure 3 shows a schematic representation of the image indexing and query process. Image indexing refers to the preliminary organization of the image data that must be accomplished prior to image retrieval through the query process. Our manufacturing specific CBIR software tool is a separate program that works in conjunction with either a database of images or with directories of image files. The indexing process begins by scanning all the available imagery in the database and building a table of image features, where each row in the table corresponds to one image. Several feature vectors are maintained for each image that describe independent characteristics of the scene. Once the table is generated, a process takes place that organizes the data into a tree structure that allows for rapid indexing of the imagery during the query process. Both the feature vector table and the indexing structure are maintained for use during the query process. As new images are added to the database, the feature vector table and the indexing structure must be updated accordingly.

Once the feature vector table and indexing tree are established the user performs a query by presenting the system with a new image. The image is submitted as a query after conversion to a series of feature descriptions analogous to those defined in the table. By passing the query image through the tree, a subset of the images are rapidly obtained that share similar feature characteristics. The subset is presented to the user so that other relevant images can be selected. Relevance images are those that are considered by the user to strengthen the query by providing stronger examples of the desired characteristics (e.g., defect type or substrate structure). The relevance imagery is used to weight the query process more heavily towards those characteristics that the user is attempting to locate in the database. The relevance process is iterative and the user can continue to select new relevant imagery after each pass through the indexing tree. The final result is a list and display of

images that approximately match the user's query and relevance requirements. These are displayed along with a similarity metric that indicates how similar the results are to the original query image.

Figure 3 – Schematic representation of the (a) image indexing and (b) image query process.

4. RESULTS

Figures 4 through 7 show query results that demonstrate our approach to manufacturing-specific CBIR. For these initial results, a database containing approximately 2000 images was used. The imagery was originally obtained from optical and SEM microscopy inspection tools used in the semiconductor industry. The optical images were recorded in 24-bit color format while the SEM images are 8-bit monochrome. Although this database is not sufficiently large at present to perform an in-depth analysis of the CBIR method, it does demonstrate some interesting attributes of the CBIR process as it is currently encoded.

Figure 4 shows two result windows from our CBIR software tool. The query conditions were defined to consider both the defect and substrate characteristics equally. The query images reside in the upper left-hand corner of the windows and are labeled as "Query". For this figure, the query images were obtained from an optical microscope and are in color. The window on the left side of the figure shows a query and results consisting of a patterned substrate that is geometric but irregular, i.e., the structure varies across the images. The right-hand window shows a substrate that is fairly uniform with a subtle vertical striped pattern. Note that the defect and substrate characteristics are similar across all the candidates extracted from the database. Figure 5 shows two result screens from queries that also consider both the substrate and the defect characteristics equally. In this case the query images were obtained from SEM inspection tools. Once again the characteristics of the defect region in the images is evident across all matches for both windows. The substrate characteristics have been faithfully matched as well, all except for the last image in the left-hand window that contains a similar pattern as the query but at a different scale. Note in all of these figures that a similarity metric is displayed below each query result. This metric presents the user with a relative measure of the similarity between a particular query result and the original query image.

Figure 4 – Results of a query that considered both the defect and substrate characteristics. These images were obtained using a microscope-based inspection tool and a 24-bit color camera.

Figure 5 - Results of a query that considered both the defect and substrate characteristics. These images were obtained from a SEM microscope.

Figure 6 - Results of a query that considered the substrate characteristics. Notice that the substrate regions in the images are similar while the defect characteristics broadly vary.

Figure 7 - Results of a query that considered the substrate characteristics. These results are similar to those in Fig. 6 and include both optical microscopy and SEM imagery.

Figures 6 and 7 show query results that are based primarily on the substrate characteristics, i.e., the defect characteristics were de-emphasized. Note in the left-hand window of Fig. 6 that the defects vary greatly in size. This is even more apparent in the right-hand window where the defects differ in morphology, intensity, and texture. The similarity measures that are displayed in Figs. 6 and 7 are derived only from the substrate characteristics. Figure 7 shows similar results for different substrate patterns and textures. The right-hand window in Fig. 7 shows the result of a substrate query based on a SEM image, while the other windows in Figs. 6 and 7 show optical images.

5. CONCLUSIONS

We have proposed a new field of application for CBIR that focuses on the manufacturing environment. Manufacturing imagery from automated defect analysis tools is becoming more abundant as computer systems and storage media become less expensive and as computer vision technology matures. The defect analysis systems that provide product imagery assist the CBIR process by providing the system with defect segmentation data that is useful in describing the scene in a variety of ways, e.g., in terms of the defect or the substrate characteristics. Although our manufacturing-specific CBIR results are preliminary to date, they have demonstrated that a powerful image query technique applied to the manufacturing environment is feasible. Demonstrations of queries that focus on different aspects of the manufacturing data, such as defect and substrate, have shown positive results for differentiating a broad variety of imagery within a single database. As this work continues, larger databases are being established with an even broader variety of image content that will assist us in the further characterization of our CBIR process.

6. REFERENCES

- [1] V.N. Gudivada and V.V. Raghavan, "Content-Based Image Retrieval Systems", *IEEE Computer Magazine*, 0018-9162, September 1995, p. 18.
- [2] M. De Marsicoi, L. Cinque, and S. Levialdi, "Indexing Documents by their Content: A Survey of Current Techniques", *Imaging and Vision Computing*, Vol. 15, 1997, p. 119.
- [3] Y. Gong, C.H. Chuan, and G. Xiaoyi, "Image Indexing and Retrieval Based on Color Histograms", *Multimedia Tools and Applications*, Vol. 2, 1996, p. 133.
- [4] V.E. Ogle and M. Stonebraker, "Chabot: Retrieval from a Relational Database of Images", *IEEE Computer Magazine*, 0018-9162, September 1995, p. 40.
- [5] B.S. Manjunath and W.Y. Ma, "Texture Features for Browsing and Retrieval of Image Data", *IEEE Transactions of Pattern Analysis and Machine Intelligence*, Vol. 18, No. 8, August 1996.
- [6] J. You, H. Shen, and H.A. Cohen, "An Efficient Parallel Texture Classification for Image Retrieval", *Journal of Visual Languages and Computing*, Vol. 8, 1997, p. 359.
- [7] B.M. Mehtre, M.S. Kankanhalli, and W.F. Lee, "Shape Measures for Content Based Image Retrieval: A Comparison", *Information Processing and Management*, Vol. 33, No. 3, 1997, p. 319.
- [8] J.E. Gary and R. Mehrotra, "Similar Shape Retrieval Using a Structural Feature Index", *Information Systems*, Vol. 18, No. 7, 1997, p. 525.
- [9] R. Mehrotra and J.E. Gary, "Similar-Shape Retrieval in Shape Data Management", *IEEE Computer Magazine*, 0018-9162, September 1995, p. 57.
- [10] C. Hsu, W.W. Chu, and R. K. Taira, "A Knowledge-Based Approach for Retrieving Images by Content", *IEEE Transactions on Knowledge and Data Engineering*, Vol. 8, No. 4, August 1996.
- [11] P.W. Huang and Y.R. Jean, "Design of Large Intelligent Image Database Systems", *International journal of Intelligent Systems*, Vol. 11, 1996, p. 347.

- [12] B. Tao and B. Dickinson, "Image Retrieval and Pattern Recognition", SPIE, Vol. 2916, 1996, p. 130.
- [13] M. Flickner, H. Sawhney, W. Niblack, J. Ashley, Q. Huang, B. Dom, M. Gorkani, J. Hafner, D. Lee, D. Petkovic, D. Steele, and P. Yanker, "Query by Image and Video Content: The QBIC System", IEEE Computer Magazine, 0018-9162, September 1995, p. 23.
- [14] Y. Rui, T.S. Huang, and S. Mehrotra, "Relevance Feedback Techniques in Interactive Content-based Image Retrieval", *Storage and Retrieval for Image and Video Databases VI*, IS&T/SPIE's 10th Annual International Symposium on Electronic Imaging: Science & Technology, San Jose Convention Center, San Jose, CA, January 24-30, 1998.
- [15] T.S. Newman, A. K. Jain, "A Survey of Automated Visual Inspection", *Computer Vision and Image Understanding*, Vol. 16, No. 2, pp. 231-262, March 1995.
- [16] M.H. Bennett, K.W. Tobin, S.S. Gleason, "Automatic Defect Classification: Status and Industry Trends", *Integrated Circuit Metrology, Inspection, and Process Control IX*, Proc. SPIE, Vol. 2439, p. 210-220, May 1995.
- [17] S.S. Gleason, M.A. Hunt, and W.B. Dress, "Automatic Classification of Extracted Semiconductor Defect Feature Data", ORNL/TM-12676, Martin Energy Systems, Inc., April, 1994.
- [18] K.W. Tobin, S.S. Gleason, F. Lakhani, and M.H. Bennett, "Automated Analysis for Rapid Defect Sourcing and Yield Learning", *Future Fab International*, Vol. 4, 1997, p. 313.
- [19] S.S. Gleason, K.W. Tobin, and T.P. Karnowski, "Rapid Yield Learning Through Optical Defect and Electrical Test Analysis", *SPIE's Metrology, Inspection, and Process Control for Microlithography XII*, Santa Clara Convention Center, February 1998.
- [20] K.W. Tobin, S.S. Gleason, T.P. Karnowski, S.L. Cohen, "Feature Analysis and Classification of Manufacturing Signatures on Semiconductor Wafers", *Machine Vision Applications in Industrial Inspection V*, Proc. SPIE, Vol. 3029, p. 12-25, April 1997.
- [21] K.W. Tobin, et al., "Using Historical Wafermap Data for Automated Yield Analysis", International Symposium of the American Vacuum Society, Baltimore, Maryland, November 1998.