Computers in Industry 66 (2015) 1–10

Contents lists available at ScienceDirect

Computers in Industry

journal homepage: www.elsevier.com/locate/compind

Automated visual inspection in the semiconductor industry: A survey

Szu-Hao Huang *, Ying-Cheng Pan

Department of Industrial Engineering and Engineering Management, National Tsing Hua University, No. 101, Section 2, Kuang-Fu Road, Hsinchu 30013, Taiwan, ROC

ARTICLE INFO

Article history:
Received 24 October 2013
Received in revised form 9 July 2014
Accepted 21 October 2014
Available online 22 November 2014

Keywords:
Automated visual inspection
Semiconductor industry
Wafer
TFT-LCD
LED

ABSTRACT

Automated visual inspection is an image-processing technique for quality control and production line automation. This paper reviews various optical inspection approaches in the semiconductor industry and categorize the previous literatures by the inspection algorithm and inspected products. The vision-based algorithms that had been adopted in the visual inspection systems include projection methods, filtering-based approaches, learning-based approaches, and hybrid methods. To discuss about the practical applications, the semiconductor industry covers the manufacturing and production of wafer, thin-film transistor liquid crystal displays, and light-emitting diodes. To improve the yield rate and reduce manufacturing costs, the inspection devices are widely installed in the design, layout, fabrication, assembly, and testing processes of production lines. To achieve a high robustness and computational efficiency of automated visual inspection, interdisciplinary knowledge between precision manufacturing and advanced image-processing techniques is required in the novel system design. This paper reviews multiple defect types of various inspected products which can be referenced for further implementations and improvements.

Contents

1. Introduction

Automated visual inspection (AVI) is image-processing method for quality control that has been widely applied in the production line of traditional manufacturing industries, such as for mechanical parts, vehicles, and the garment industry. The survey papers have reviewed several early inspection applications and related computer vision techniques, which consist of image representation, template matching, and pattern classification algorithms [1,2]. With the rapid development of computers and digital image-capturing devices in recent years, real-time optical inspection systems have also been realized in current precision production

* Corresponding author. Tel.: +886 3 574 2353; fax: +886 3 574 2353.
E-mail address: shhuang@ie.nthu.edu.tw (S.-H. Huang).

http://dx.doi.org/10.1016/j.compind.2014.10.006
0166-3615/

and assembly lines. This paper reviews various automated visual inspection approaches and related techniques in the semiconductor industry.

In most manufacturing industries, one goal is to achieve 100% quality assurance of the parts, subassemblies, and finished products, especially in mass-production industries. Product inspection is an important step in the manufacture process, and how to ensure that the quality of each product meets the standard is a challenging task. However, inspection tasks are time consuming, and mostly performed by human inspectors. The performance of the inspectors is inadequate, and the accuracy is often affected because of the fatigue of perfunctory task; moreover, human inspectors require training, and skills require time to develop. Compared to machines, the working hours of human inspectors are relatively short, and the cost of labor is a main consideration factor for manufacturers as well.

The electronics industry plays a vital role in modern precision engineering and manufacturing, which includes the design, layout, fabrication, assembly, and testing of various semiconductor components and products. The major products manufactured by the semiconductor industry include wafers, thin-film transistor liquid crystal displays (TFT-LCDs), and light-emitting diodes (LED). Because of growing competition and a decreasing gross profit margin, manufacturing process automation is critical for reducing production costs and improving efficiency. Over the past 15 years, the fabrication technology node used by the semiconductor industry has improved from 130 nm to 14 nm. Quality control and automated visual inspection systems employed in precision manufacturing have also been discussed widely to facilitate developing novel manufacturing techniques. The automatic visual inspection system is among the most critical automation tools used to reduce the labor force and increase yield rates. The goal of this survey was to study state-of-the-art AVI techniques and review several previous effective systems used by the semiconductor industry. In addition, this paper assesses various inspection products and related applications, and can be a reference for implementing and improving future manufacturing processes.

AVI has been developed for decades; the system can detect the same type of surface-related defect. The object or the product would be inspected by sensors, and visual data would be collected and returned to the system for analysis. The inspection process often involves a measurement of assembly integrity, surface finish, and geometric dimensions. Compared to the effectiveness of manual inspection, AVI is a desirable choice. Advances in technology and manufacturing devices have resulted in cheaper industrial visual inspection equipment. With better sensing devices and automatic equipment and a combination of computer technology, including pattern recognition, image processing, and artificial intelligence, an automatic inspection system can run in real time and be consistent, robust, and reliable. The use of an AVI increases productivity and improves product quality as well. In addition to ensuring product quality control, an automated inspection system can also gather statistical information to provide feedback to the manufacturing process.

As computer vision-based inspection has become one of the most important application areas, numerous related studies and works have been conducted, including on the conditions of hardware, the development of software, and related applications. Chin and Harlow surveyed AVIs from 1972 to 1980, including the application on Printed circuit boards (PCBs), photomasks, and integrated circuits [1]. They also discussed the system and the non-electrical industry. Chin conducted a survey following related development in the 1980s [2]. Thomas et al. provided a review of related works from 1973 to 1994 [56]. They focused on the machine vision algorithm, illumination, schemes, and real-time performance and verification. Newman and Jain also reviewed relevant works from 1988 to 1993 [57]. They especially focused on the CAD applied in AVI and the system. Malamas et al. classified applications into two parts: inspected features of the industrial product or process and the inspection independent characteristics of the inspected product or process [25]. They also reviewed the software and hardware tools of industrial vision systems.

Some of the studies focused mainly on specific products or techniques applied in automated inspection. Moganti et al. reviewed the algorithms and techniques applied in PCB AVIs [11]. Markou and Singh provided an overview of approaches of novelty detection, including the statistical approach and neural network (NN)-based approaches [23,24]. Kumar focused on the application on fabric defect detection, and presented a survey on the available techniques for the inspection of fabric defects [44]. Xie reviewed texture analysis techniques used in surface detection, and also discussed color texture analysis [45].

These studies presented an overview of automated inspection development in the past few decades. Advances in equipment, technology, and the methods applied in AVI have been significant. Moreover, manufacturing technology has improved; precision manufacturing has been gradually developed, such as micro-precision manufacturing and nano-manufacturing. Semiconductor fabrication technology advanced from micrometers to nanometers in a few years, and currently, the 14 nm manufacturing technology has been achieved. Product inspection requirements have become stricter and more challenging as products become smaller, and the assembly process is increasingly precise. However, studies investigating the application of AVI in the semiconductor industry are few, and a comprehensive survey has yet to be conducted. Therefore, this paper reviews the applications and related analysis algorithms of semiconductor product inspection developed between 2000 and 2013. AVI systems feature several specific elements designed to suit the unique characteristics of semiconductor products. Because the inspected electronic components may be composed of compound materials, such as silicon, germanium, and gallium, the complex image texture [8,16,50] contains abundant information that must be analyzed and understood. Moreover, precise inspection of nanometer-scale objects may require a high-quality imaging system. For high-resolution images, multiscale and super-resolution techniques [55] have been proposed to reduce time consumption. Various researchers have focused on the path planning in AVI systems [48] or on parallel computation [8,31,39] applied to increase system efficiency. In addition, designing special-purpose light sources or changing the image acquisition equipment may simplify the image analysis problems. For example, laser beams [3] and magneto-optic images [62] have been used to inspect semiconductor surfaces featuring special materials, such as translucent wafer.

In addition to the survey papers [1,2,11,23–25,44,45,56,57], previous literature was reviewed using two parallel methodologies. First, inspection algorithms were classified into four major categories: projection methods, filter-based approaches, learning-based approaches, and hybrid methods. Section 2 introduces these algorithms and reviews related previous studies, which are summarized in each subsection. Second, inspected products and applications used in the semiconductor industry were investigated. Semiconductor products discussed in previous studies can be classified into three categories: wafers, TFT-LCDs, and LEDs. Section 3 discusses the related studies and product defects. The current paper presents a profile of AVI systems used in semiconductor industry. Reviewing relevant literature using the two classifications of algorithms and products can clearly determine the algorithm characteristics, and also enable companies to select proper algorithms for developing their own inspection systems for manufacturing. Fig. 1 displays a review methodology tree showing the paper organization and related studies in each leaf node.

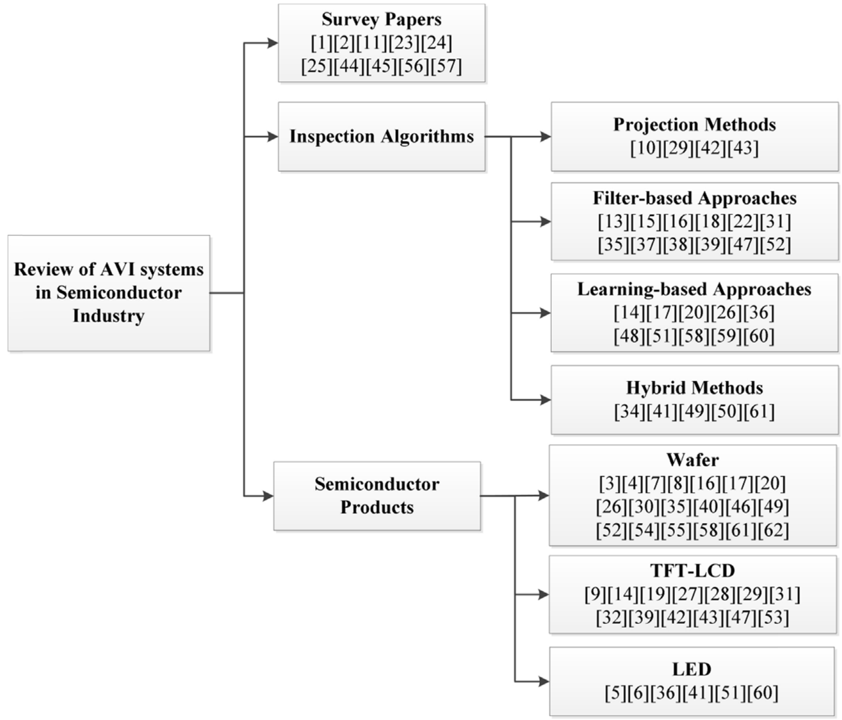

Fig. 1. The review methodology tree and related previous works.

2. Visual inspection techniques

Most traditional AVI systems adopted simple image subtraction or template-matching methods to measure the difference between a predefined referenced pattern and clipped windows from captured images. In recent years, several novel image-processing and classification techniques have been applied to solve more critical inspection problems in the precision engineering and manufacturing industry. The proposed systems can be categorized into four of the following major groups according to the techniques they adopted: projection methods, filter-based approaches, learning-based approaches, and hybrid methods. The related works of each group are listed in Table 1 and summarized in the following subsections.

Table 1
List of the visual inspection papers in semiconductor industry.

Category	Algorithms and Methods	Papers
Projection methods	Principal component analysis	[10,29]
	Independent component analysis	[42,43]
Filter-based approaches	Discrete cosine transform	[15,35]
	Wavelet transform	[13,16,18,22,37,38,52]
	Fourier transform	[39]
	Fourier and wavelet transform	[31]
	Discrete cosine and wavelet transform	[47]
Learning-based approaches	Neural networks	[17,20,26,36,48,51,58–60]
	Genetic algorithms	[14]
Hybrid methods		[34,41,49,50,61]
Review of automated visual inspection		[1,2,11,23,24,25,44,45,56,57]

2.1. Projection methods

The basic concept of projection methods is to model the correlation between learning samples and to determine a more discriminative space to represent these samples. After a simple re-projection process, the redundant information and noise are reduced, and the hidden information is revealed. Several well-developed eigen-based methods, such as principal component analysis (PCA), linear discriminant analysis (LDA), and independent component analysis (ICA), are widely applied to estimate the transformation methods of sample projection. In addition, the similarity between samples and the inspection rules are easily measured in the projected feature space.

Thin-film transistor (TFT) LCDs play a dominant role in modern display devices. To inspect surface defects on TFT panels that caused visual and electrical failure, Lu and Tsai proposed an AVI method based on PCA [29]. The image is treated as a matrix of pixels and singular value decomposition (SVD) is used to represent different degrees of image detail. The singular values are selected to represent the background texture of the surface, and the image is reconstructed by setting the singular values to zero. The periodical and repetitive patterns can be effectively eliminated from the textured image. Chen and Perng proposed an approach by using PCA to inspect defects in directionally textured surfaces [10]. The image is divided into an ensemble of horizontal scan lines, and the input space is turned into the principal component space. The linear primitives associated with the first k major components and corresponding weight vectors were determined by the normalized-eigenvalue-greater-than-one criterion, and were reconstructed as a corresponding truncated component solution for texture approximation. The local defects were revealed by applying image subtraction between the original image and the TCS, and the textures were removed in the final image while any original defect was distinctly preserved.

Tsai and Lai presented a self-comparison scheme to detect defects on structural surfaces containing periodic complex patterns

[42]. The proposed method can be directly applied to a 1D line image that is divided into two segments of equal length. Combined with the techniques of the probability density function and particle swarm optimization (PSO), the proposed ICA model can be well suited for translation recovery between two signals with the same periodic pattern. Normalized cross-correlation (NCC) is also adopted to measure the similarity between two compared segments. This method is computationally efficient because of the small size of the de-mixing matrix, and it shows an efficient outcome in the inspection of periodically patterned surfaces. A machine vision-based approach for automatic detection of micro-defects was proposed by Lu and Tsai to inspect periodically patterned surfaces, especially in TFT-LCDs [43]. ICA is applied to determine the de-mixing matrix and the independent components that are treated as representatives of the structure of the patterned image. The row vectors that correspond to the ICs are excluded, and the row vectors associated with the ICs that represent the uniform background are preserved. The reformed de-mixing matrix is then used to reconstruct the TFT-LCD image. The proposed method requires no quantitative features or reference templates, and it is believed to be extended for defect detection in patterned surfaces containing periodic patterns. However, its sensitivity to the vertical shift and its inability to preserve the size and shape of a detected defect are the drawbacks of the proposed method. Serdaroglu et al. presented a method for defect detection based on the combination of wavelet transform and ICA, and the detailed introduction is described in Section 2.4 on hybrid methods [34].

2.2. Filtering-based approaches

Filtering-based approaches are widely applied in signal-processing applications. Various AVI systems based on image enhancement and image restoration techniques adopt spatial filtering methods to improve the resolution and quality of optical systems. Moreover, frequency-filtering techniques, which include low-pass filters and high-pass filters, are commonly used to process repetitive image patterns and noises. Transforming signals from an original spatial domain to a frequency domain by multiple mathematical transformation functions, such discrete cosine transformation, wavelet transform, and Fourier transform, is the first step for further analysis.

A pinhole is one type of common surface defect that frequently occurs in manufacturing. Lin and Ho presented a discrete cosine transform (DCT)-based method, and focused on the inspection of tiny pinhole defects in randomly textures surfaces of SBL chips [35]. The proposed means can effectively attenuate the global random texture pattern, and only the images of tiny pinhole defects are restored. Furthermore, they developed two accumulative sum detection procedures that can determine the best high-pass filtering parameters automatically. Experimental results demonstrated that the approach is invariant to the orientation of the target chip, and achieves high accuracy in detecting pinhole defects. Perng and Cheng proposed a method using DCT to detect defects in directionally textured surfaces [15]. The input image is transformed into the DCT domain, and the linear primitives associated with high energy in the DCT domain are eliminated by reducing to zero. The defects are extracted using the thresholding method, which is based on statistical process control binarization. In the final image, the original textures are removed, and the defects are preserved. Moreover, the approach is insensitive to image shifting, image rotation, and changes in illumination. Fig. 2 shows the inspected images and restored output with DCT transformation. It is applied in the pinhole, scratch, and erosion defects detection problem from the inspected images of textured OLED panel.

Kim et al. proposed an inspection system consisting of CCD array cameras and a scanning algorithm based on wavelet transform [13]. The wavelet transform is used to extract features, and the signal-to-noise ratio (SNR) is calculated based on the results. The wavelet coefficients are optimized by learning routines. Tsai and Hsiao presented a multi-resolution approach for the inspection of local defects embedded in homogeneous textured surfaces [18]. Instead of using local textural feature extraction, and the wavelet transform was introduced to achieve efficient image restoration. The sub-images are selected in different decomposition levels for a backward wavelet transform, and repetitive texture patterns are removed, but the local anomalies are enhanced in the restored image. However, the task of automatic selection of the number of multi-resolution levels and the decomposed sub-images for defect detection remains under investigation. Tsai and Chiang conducted research on inspecting defects embedded in homogeneous textured surfaces in later years, and presented an approach based on the wavelet transform [22]. They developed a wavelet band selection procedure that can automatically determine the number of resolution levels and decompose sub-images for the best discrimination of defects. Inspired by the characteristic of the high frequency of repetitive patterns and the removal of texture from the original image, Han and Shi presented an effective approach based on the wavelet transform to detect defects in images with a high-frequency texture background [37]. The input image is decomposed by the wavelet transform, and the sub-image is reconstructed by selecting an appropriate level. An adaptive level-selecting scheme is developed on the basis of analyzing co-occurrence matrices of the approximation sub-images.

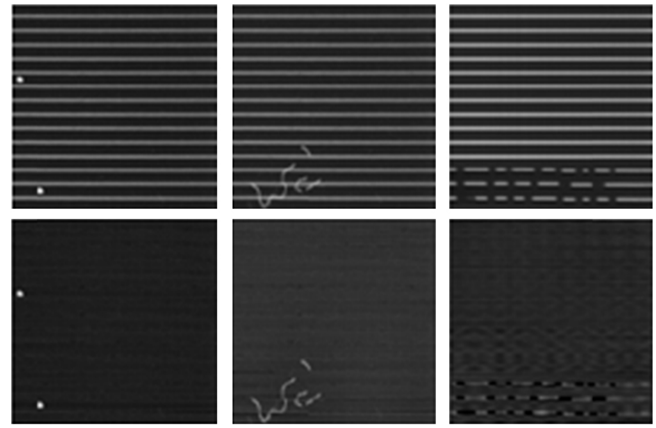

Fig. 2. The examples of pinhole, scratch, and erosion defects detection from a textured image of OLED panel [15].

Unstructured appearances and low-intensity contrast are the difficulties of ripple defects to be inspected. To inspect ripple defects in surface barrier layer chips as shown in Fig. 3, Lin presented a method based on the Haar wavelet transform. The wavelet transformation is used to decompose an image and the wavelet characteristics are used to describe surface texture properties [38]. Three different multivariate statistics of Hotelling, Mahalanobis distance, and chi-square are applied to integrate the multiple texture features and judge the existence of defects. To detect visual defects on semiconductor wafer dies, Yeh et al. proposed an approach based on a 2D wavelet transform [52]. The image is decomposed by 2D wavelet transform at multiple scales and different wavelet bases. The wavelet transform modulus sum is used to detect visual abnormalities because irregular edges preserve more wavelet energy, and the interscale ratio is less than a predefined threshold. The proposed method is template-free and easy to implement, and it is suitable for product varieties and small-batch production. Li and Tsai focused on the inspection task of multicrystalline solar wafers [16]. The main difficulty is the inhomogeneous texture of the wafer surface, and the defects found

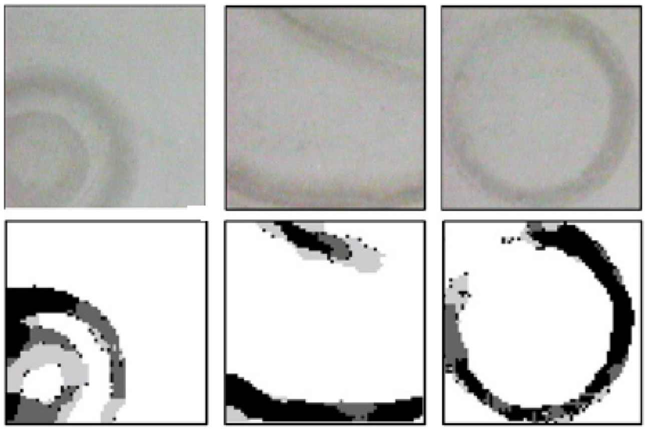

Fig. 3. Example ripple defect images and the detection results of the wavelet based method [38].

in a solar wafer surface generally involve scattering and blurred edges. To address this problem, they presented a defect detection scheme based on wavelet decomposition techniques. To distinguish local defects from the crystal grain background, they used the wavelet coefficients as features and the difference of the wavelet detail sub-images in two consecutive decomposition levels as weights. Their method can be applied successfully to any defect type on inhomogeneous solar wafers, and solve the problem faced by traditional wavelet transform techniques for texture analysis as well. Li combined the concept of the wavelet transform, rough set theory, and support vector machines (SVM) on surface defects detection [50]. Serdaroglu et al. presented a method for defect detection based on the combination of wavelet transform and independent component analysis [34]. Tsai et al. proposed a non-referential defect detection approach of TFT-LCDs by using Fourier image reconstruction [39]. The 1D gray-level line image is divided into small segments, which are then combined as a 2D image. By eliminating the frequency components in the 2D Fourier spectrum, and back-transforming the image using the inverse Fourier transform, the process can effectively remove the complex background pattern and preserve local anomalies adequately. To inspect micro-defects in patterned TFT-LCD panel surfaces, Tsai and Hung presented a 1D Fourier-based image reconstruction approach that worked directly on 1D input images [31]. Fourier transform can effectively remove patterned backgrounds and distinctly preserve local anomalies, and Haar wavelet decomposition is applied to remove uneven illumination in the filtered image, so that defects can be easily segmented with simple statistical control limits. Chen and Chou proposed two methods based on DWT and DCT to detect mura defects on LCD panels [47]. Results shows that DWT is superior for filtering the regular structure, and DCT is better for detecting luminance variation in large areas.

2.3. Learning-based approaches

Learning-based approaches are developed with machine-learning and pattern recognition algorithms. The goal of machine-learning systems is to automatically collect discriminative rules and improve accuracy with training samples. The concepts of learning algorithms result from various research fields, such as statistics, artificial intelligence, philosophy, and information theory. Several AVIs based on well-known learning methods, including artificial neural networks (ANNs), support vector machines (SVMs), and genetic algorithms (GAs), are reviewed in this section.

Wafer bin maps are often used to track the root causes of failure. However, many companies still rely on the manual approach, which is not only time-consuming, but also inefficient. To solve this problem, Wang presented a hybrid framework integrated with spatial statistics and filtering, kernel decomposition, and support vector clustering [49]. Li presented a multi-resolution approach to solve the problem of detecting small surface defects of texture patterns [50]. The method is based on the integration of the DWT, inverse DWT, and rough set theory with the SVM classifier. Xie et al. proposed a detection method based on SVMs to identify the defect types, such as rings, semicircles, scratches, and clusters. Their proposed method can work correctly in noisy images with the variations of defect locations and angles [58].

Chen and Liu proposed a system to recognize defect spatial patterns to inspect semiconductor fabrication [17]. The method is based on the NN architecture named the adaptive resonance theory (ART) network. They also conducted another approach called the self-organizing map, which was also conducted to compare efficiency, and the results show that ART can recognize defect spatial patterns more easily and correctly. To ensure defect-free dies of post-sawing semiconductor wafers, full inspections are usually conducted. However, misjudgment may occur in the inspection, and the task is costly. Su et al. proposed an NN approach for post-sawing inspection [20]. Three types of NNs, including backpropagation NN (BPNN), the radial basis function network (RBFN), and learning vector quantization, are proposed and tested. The result shows that their method can efficiently reduce the inspection time to 1 s per die. In traditional quality control process, the color filter of LCD panel is visually inspected by operators. Kuo et al. combined BPNN and Taguchi method to optimize the feature learning process and create more discriminative classifier. Four different features, including area, aspect ratio, squareness ratio and damage ratio, were used to describe the defect attributes [59]. Wafer bin maps (WBMs) are important for yield improvement to trace root causes. Chen et al. [26] presented a new algorithm that adopted a supervised learning methodology to develop an online WBM pattern recognition system. A supervised feed-forward NN was selected as the learning model for center failure, edge failure, and local failure, and two indices were set to verify the performance of the supervised NN. The method can also detect repeating failures that are usually viewed as random patterns in existing approaches.

Chen and Hsu applied the NN-based recognition system for automatic LED inspection [36]. Two types of NNs, the BPNN and the RBFN, were proposed and tested. The accuracy of recognition is 100% for the BPNN and 96% for the RBFN, and the testing speed of the approach is almost 1.5 times faster than the traditional inspection system. To facilitate the detection of defective dies in LED wafer images, Chang et al. proposed a method consisting of two Hopfield NNs, a contextual-HNN, and a competitive-HNN [51]. The identification task of the LED die regions are based on the contextual-HNN, which considers the surrounding information of a pixel. A competitive-HNN, which considers the global intensity distribution of an image, is used to cluster the die into three groups. A two-stage BPNN method was proposed by Kuo et al. to detect the fragment and scratch defects of LED chips [60]. The NCC algorithm and K-means clustering are used to localize the object of interest and extract the representative features, respectively. Wu et al. presented a method to optimize the position accuracy and path-planning problem of a PCB [48]. They set the problem of path planning as a traveling salesman problem, and the proposed approach is based on the Hopfield net algorithm to address the problem.

Saitoh proposed a method to detect brightness unevenness in LCD displays [14]. A visual continuous boundary is extracted from the input image by using the GA based on perceptive grouping factors. The result shows that the extracted boundaries of brightness unevenness had similar forms to perceived brightness unevenness by the visual sense.

2.4. Hybrid methods

For several complex and difficult tasks, the system combines various types of techniques to achieve inspection. This type of method is called a hybrid method.

Serdaroglu et al. presented a method for defect detection based on the wavelet transform and ICA [34]. The method uses the wavelet transform first to obtain defect-free subwindows, and the independent components of these subbands are calculated as basis vectors. Wafer fabrication is a complex and costly, process and IC chips fabricated on semiconductor wafers are highly vulnerable to clustered defects. Engineers usually use the WBM, on which various types of defect patterns are shown, to identify the root causes of failure. Wang presented a hybrid approach that integrates spatial statistics, kernel-based eigen-decomposition, and support vector clustering to estimate the number of defect clusters [49]. The results show that the method can separate both convex and non-convex defect clusters simultaneously, and successfully extracts and separates four types of composite defect patterns. In addition, the proposed approach attempts to facilitate the research gap and requires relatively few data samples to achieve a better performance. To solve the problem of detecting small surface defects of texture patterns, Li presented a multi-resolution approach which is based on the integration of the DWT, inverse DWT, and RST with the SVM classifier [50]. The subimage and detail subimages are smoothed by properly selecting the wavelet bases and the number of decomposition levels, and features are selected based on the rough set feature selection algorithms that can address vagueness and uncertainties. The features are then nonlinearly mapped into the SVM architecture, which separates one class from all the others, or separates each pair among all classes. Chen et al. addressed a two stage inspection approach to implement the inspection system of in-tray semiconductor chips [61]. The image alignment algorithm was first adopted to regulate the location of the inspected image, and a hybrid approach combining adaptive image difference and design-rule strategy was used to detect the defects of semiconductor chips.

2.5. Miscellaneous algorithms

Several previous systems could not be classified into the discussed categories. Motivated by developing an efficient and effective template-matching method that can tolerate variation, Tsai et al. presented a shift-tolerant dissimilarity measure method based on optical flow techniques [41]. With a represented template, the optical flow field between the template and the test image are evaluated. The degree of difference is calculated by the dissimilarity measure of each pixel, and the integral image technique is applied to replace the sum operations in optical flow computation. The proposed approach is insensitive to minor shifts, and is robust to misalignment or random product variations. The approaches based on template matching are applied to defect detection, and they can also conduct defect classification according to predefined defect types. Rau and Hu presented an image subtraction-based inspection method for detecting defects on the inner layer of PCBs [33]. They combined the inspection process with CAD files to accelerate computation and to compose an ideal reference image. Outer boundary tracing and boundary state transition (BST) methods are used to identify defect types. The defects are divided into eight types: open, mouse bite, pinhole, missing conductor, short, spur, excess copper, and missing hole. Perng et al. focused on LED defects that are unavoidable in fabrication and taping processes [6]. Instead of human visual inspection, they proposed a machine vision system that combines an automatic system-generated inspection regions (IR) method to inspect two types of LED surface-mounted devices (SMDs). The process is divided into two stages: the pre-training stage and the testing stage. In the pre-training stage, the IR is specified, and the related parameters are obtained, and Otsu's auto-thresholding method and the closing operation are applied to the images. In the testing stage, normalization and segmentation are applied on the testing images of inverse polarity, mouse bites, missing gold wires, and surface defects, and on the testing images without defects. The experimental result shows that the method could detect defects with an accuracy of up to 95% for each type of SMD LED. The heterogeneous texture in the image of a multicrystalline solar wafer results in great difficulty to perform defect detection. To address this problem, Tsai and Luo presented a method based on mean-shift techniques [8]. The grain edges are enclosed in a small spatial window, and defect region shows a high variation of edge directions. After converting the gray-level image to an entropy image by calculating the entropy of gradient directions, the mean-shift smoothing procedure is performed to remove noise and defect-free grain edges. The suspected edge points in the filtered image are identified as defects by using an adaptive threshold. Li and Tsai proposed a Hough transform-based method to identify low-contrast defects in images that are unevenly illuminated, and focused on the inspection of the mura defects in LCD panels [9]. The method works on 1D gray-level image, and an idea line of a profile is used to verify defects, which results in a non-stationary line signal in the unevenly illuminated image. The revised Hough transform is then applied for line detection, which can accommodate a distance tolerance. Any point with the distance to the line falling within the tolerance is accumulated by regarding the distance as the voting weight. In addition to the usage of raw images captured by CCD camera directly, Pan et al. presented a defect detection based on the magneto-optic images [62]. Several image enhancement and segmentation algorithms had been applied to improve the image quality with noise removal.

3. Inspected products in the semiconductor industry

The semiconductor manufacturing process can be divided into three major phases. In the first phase, raw materials (silicon or germanium) are transformed into cylindrical ingots using the Czochralski growth method. After slicing, polishing, lapping, and etching, the ingots are sliced into wafers. The AVI systems can be adopted to ensure the flatness and completeness of the wafer surface. In the second phase, the integrated circuit mask design is projected onto the wafer surface by diffusion, lithography, chemical–mechanical planarization, deposition, or etching. A wafer acceptance test is applied to examine the effectiveness and stability of every wafer die. In the final phase, the wafers are cut into chips, and the manufacturing is completed with packaging processes, including die saw, die bond, wire bond, mold, planting, and marking. The visual inspection during the third phase should detect various defects of the products composed of multiple materials. This section describes the inspected products and applications used in the semiconductor industry, including wafers, LCDs, and LEDs. Related works and inspected defects are reviewed and discussed in each subsection.

3.1. Wafer

Manufacturing technology matures daily. The task of inspection has become a popular topic in the industry. The structure of wafers is complex, causing inspection to become more difficult. A wafer is composed of silicon or gallium arsenide, and is composed of layers of metal and other chemical materials. In semiconductor manufacturing, a wafer consists of repeated dies, which have the same structure and electrical components. Based on the property that all the dies show the same pattern, the simplest inspection algorithm is used to compare die by die for inspection defects. Defects of wafers include foreign particles, scratches, and stains, which influence the yield rate and the quality of the product.

Ohshige et al. presented a surface defect inspection system based on the spatial frequency-filtering technique [4]. The method can effectively detect sub-micro-defects or foreign particles on wafers. Khalaj et al. proposed a novel technique for detecting defects in a periodic 2D signal or image [7]. The method works efficiently for detecting the location of irregularities and defects of repeated-pattern semiconductor wafers. Shankar and Zhong proposed a template-based method for wafer die surfaces, where good dies are trained and sustained as template dies for the whole wafer [30]. The results show that the method can detect flaws as small as two-thousandths of an inch on parts of up to 8-in. wafers. To defect visual defects such as particles, contamination, and scratches on semiconductor wafer dies, Yeh et al. proposed an approach based on a 2D wavelet transform (2D WT) [52]. The method is suitable for products with high varieties and small-batch production. A pinhole is a common defect of wafer surfaces. To improve the inspection task of pinholes, a DCT-based method was proposed by Lin et al. [35]. They focused on tiny pinhole defects in randomly textured surfaces of SBL chips. The approach can effectively attenuate the global random texture pattern and accentuate only tiny pinhole defects in the restored image.

Because of the detection difficulty caused by cluster defects, such as scratches, stains, or localized failed patterns, Huang presented a new method to solve the problem [40]. An automatic wafer defect cluster algorithm was presented using a self-supervised multilayer perceptron to detect defects and mark all defective dies. Wafer bonding is a packaging technology for the fabrication of microelectromechanical systems, nano-electromechanical systems, and other semiconductor fields. However, the particles or air gap on the wafers referred to as unbonded areas are between the wafers, and result in the failure of semiconductor devices. Jang et al. developed a system that inspects wafer bond integrity by analyzing laser beam transmittance deviations and the variations in intensity caused by the thickness [3]. The method is feasible for inspecting all areas of bonded surfaces simultaneously. Common defect types of wafer post-sawing include cracks, scratches, ink spots, foreign material pollution, and pad discoloration. To ensure defect-free dies of semiconductor wafers, post-sawing usually requires full inspection. Su et al. presented an inspection approach based on three ANNs [20]. The results show that the inspection time can be efficiently reduced to 1 s per die. Spatial patterns formed by the defects on the wafer are clues for the identification of equipment problems or process variations. Chen and Liu proposed a system to recognize defect spatial patterns, to inspect semiconductor fabrication [17]. The method is based on the NN architecture named the ART network. With the development of semiconductor technology, Usuki et al. considered the development of inspection techniques for the next generation [55]. They presented a super-resolution optical inspection method by combining the standing wave illumination shift method with dark-field imaging technology, and the defects on a sample surface were effectively detected with super resolution. Xie et al. adopted SVM algorithm to recognize four common defects of wafer: scratches, semicircles, clusters, and rings [58]. The SVM-based method can deal with the misjudgment problems due to the image rotation and translation. In addition, Chen et al. mainly focused on the inspection task of in-tray chips in semiconductor industry [61]. Their proposed approach included two major stages, named as alignments stage and inspection stage, which combines the adaptive image difference method and the design-rule strategy.

WBMs are formed during the manufacturing process, and contain crucial information for engineers to trace root causes. Various types of defect patterns include scratches and rings shown on the WBMs. Chen et al. presented a new algorithm that adopted a supervised learning methodology to develop an online WBM pattern recognition system [26]. The proposed method can also detect repeating failures that are usually viewed as random patterns in the existing approaches. To estimate the number of clusters in advance, and to separate convex and non-convex defect clusters at the same time, Wang presented an inspection method based on spatial filters, entropy fuzzy c means, and spectral clustering [46]. Lastly, a decision tree based on two selected cluster features was generated for decision support. Wang proposed a hybrid approach that integrates spatial statistics, the kernel-based eigen-decomposition method, and support vector clustering to extract and separate composite defect patterns from WBMs [49]. The results show that the proposed method can separate both convex and non-convex defect clusters simultaneously, and successfully extracts and separates four types of composite defect patterns.

With growing concern for the environment, solar power has been developed to become an alternative source of electricity. Solar cells that convert energy to electricity are mainly based on crystalline silicon, and multicrystalline solar wafers are popular for use. However, the wafer surface shows a heterogeneous texture in the image, and makes detection tasks difficult. Tsai et al. presented an anisotropic diffusion scheme to detect micro-cracks in wafers [54]. They concentrated on micro-cracks that can be visually observed. The method shows great performance on the test of wafer images, and achieves a fast computation of 0.09 s for a 640×480 image. Tsai and Luo focused on the surface quality of a solar wafer that is highly related to the conversion efficiency of solar cells [8]. They proposed a mean-shift technique that easily identifies defects on a filtered image. The method performs well for identifying fingerprints and contamination defects in multicrystalline solar wafers. However, it cannot be applied to detect other defects such as cracks that present low variation in the gradient direction. Li and Tsai proposed a defect detection scheme based on wavelet decomposition techniques that can effectively distinguish local defects from crystal grain backgrounds [16]. The method can be applied successfully to any defect type that involves relative scattering and blurred edges on inhomogeneous solar wafer images, including fingerprints, contaminants, and saw-mark defects, and it can solve the problem of traditional wavelet transform techniques for texture analysis as well. Fig. 4 shows the example detection results of defective solar wafer images with fingerprint.

3.2. Thin-film transistor liquid crystal display

Large TFT-LCD devices have become important in recent years, and they are widely applied as monitors or viewfinders for different types of applications. Common LCD defects include mura, pinholes, scratches, and particles. Saitoh proposed a method to detect brightness unevenness in LCD displays [14]. An edge detection algorithm is used to identify discontinuous points, and the boundary of the brightness region is extracted using a GA. Lin et al. presented an online inspection system for LCD light guide plates to detect the degree of uniformity of light reflection [19]. The software and hardware are adequately designed, and can be applied to different types of backlight modules. An algorithm is presented in the searching and statistic process of bright spots as well. Kuo et al. presented a Taguchi-based BPNN approach to automatically detect the common defects in colour filters of LCD panel, including fibre, particle, gel, and resist coating [59].

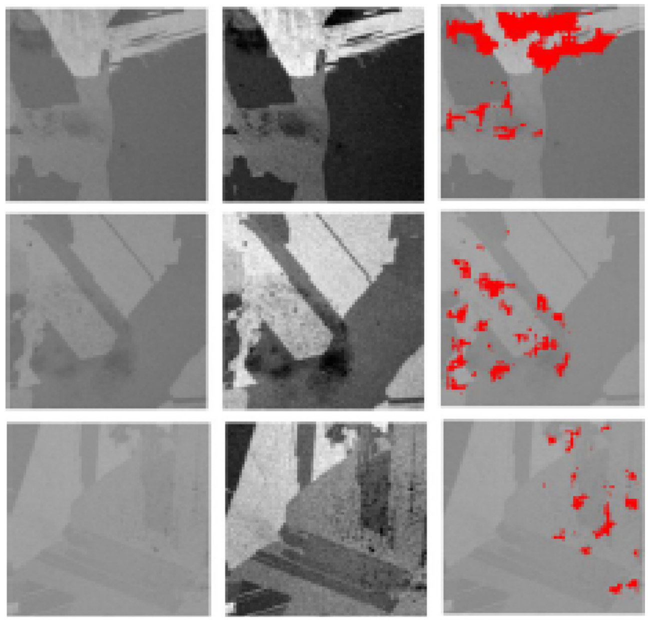

Fig. 4. Example inspected images, restored images and detection results of defective solar wafer with fingerprint [16].

Kim et al. classified spot-type defects of LCDs into macro- and micro-defects, and established different inspection stands for these two types of defects [27]. An adaptive multilevel thresholding method was proposed to segment the macroview defect from the background surface. Because the defects of TFT-LCDs are extremely complex, and the determination of the defects is a complex process that is easily influenced by observers, Zhang and Zhang presented an online detection method, which is based on a fuzzy expert system approach and can effectively detect point defects, line defects, and region defects in panels [28]. Surface defects of TFT-LCDs cause visual failure, and also electrical failure. Lu and Tsai presented an approach for the AVI of surfaces inspection [29]. Their proposed method is based on a global image reconstruction scheme based on singular value decomposition rather than feature extraction methods. The result shows that the method is successful in the detection of pinholes, scratches, particles, and fingerprints. To inspect micro-defects including pinholes, scratches, and particles in patterned panel surfaces, Tsai and Hung presented a 1D Fourier-based image reconstruction approach, and wavelet decomposition was applied to remove uneven illumination [31]. Tsai et al. proposed a non-referential defect detection approach by using Fourier image reconstruction [39]. The result shows that the proposed method is insensitive to illumination changes, and works reliably for detecting various micro-defects in different regions of the panel surface. Tsai and Lai proposed a self-comparison scheme to detect defects on structural surfaces containing periodic complex patterns [42]. Based on the model of independent component analysis, and with the use of probability density function and particle swarm optimization, the proposed method is computationally efficient. Normalized cross-correlation was adopted in the process as well. Lu and Tsai proposed a machine vision approach for the detection of micro-defects in periodically patterned surfaces [43]. The method is based on ICA, which can detect micro-defects including pinholes, scratches, and particles in panel surface. The proposed method can also be extended to detect patterned surfaces that contain periodic patterns. Fig. 5 shows various defect examples and inspection results in TFT-LCD panels. However, it is sensitive to the vertical shift of the inspection image, and cannot preserve the size and shape of the detected defect.

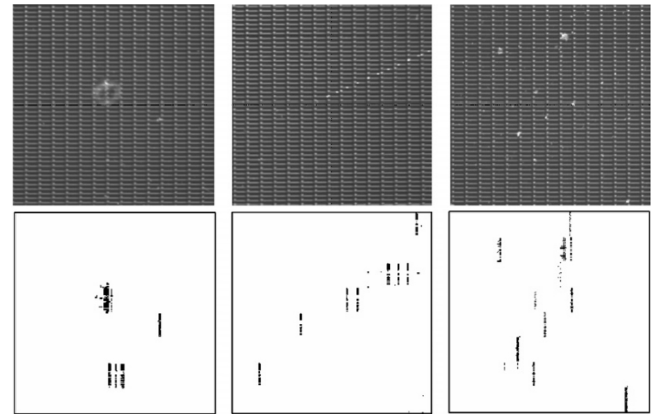

Fig. 5. The example defective TN TFT-LCD images with pinhole, scratch, and particles [43].

Mura is one of the main defects of LCDs manufacturing, and is originally a Japanese word. Mura denotes a local brightness non-uniformity, and results in an unpleasant sensation to human vision. Mura can be classified into several categories, including line-mura, spot-mura, and region-mura. Region-mura is the most difficult defect to detect because the region-mura possesses a large area of inspected image, and shows smooth changes of brightness. Jiang et al. proposed an approach based on analysis of variance, and exponentially weighted moving average techniques to detect mura-type defects [32]. The panel is divided into 144 areas, and five points are measured to obtain luminance. The proposed method can help manufacturers reduce the variation in inspection results. Chen and Chou proposed two methods based on the discrete wavelet transformation and discrete cosine transformation to detect mura defects [47]. The result shows that the DCT-based method is preferable for large-area brightness variation, and DWT is preferred for small areas. Fan and Chuang presented a computationally efficient method based on regression diagnostics [53]. Prediction error sum of squares (PRESS) residuals and an image estimation procedure were used for automatic Mura inspection of TFT-LCD devices. The method performs at the speed of 0.8 s for a 200×200 image, and the method returns lower false alarm rates as well, providing the great contribution of lower costs. To effectively identify low-contrast defects in images that are unevenly illuminated, Li and Tsai proposed a Hough transform-based method [9]. The proposed method can detect various mura defects including spot-, line-, and region-mura. However, the method considers only non-stationary straight-line detection, and cannot detect in non-stationary curved profiles and non-stationary linear/curved surfaces.

3.3. Light-emitting diode

Light-emitting diode (LED) technology has been developed for decades, and is now applied in different areas, such as vehicle lights, general illumination, and streetlamps. After the functional inspection which examines the electronic characteristics and illumination performance, the dies should be visually inspected with operators by using electrical microscopes. However, the inspection process of failed diodes is complex, and the existing inspection methods are time-consuming. The common defect types include missing components, incorrect orientations, and inverse polarity.

Chen and Hsu presented a neural networks-based recognition system for automatic LED inspection [36]. Two types of neural networks, BPNN and RBFN, were proposed and tested. The results show that the BPNN-based approach has an accuracy of 100%, and the RBFN-based approach has an accuracy of 96%. Moreover, the method needs only half the time required by the traditional system. The number of dies on an pannel is up to 80,000, leading to high labor and production costs for checking defects. To address this problem, Chang et al. proposed a method based on Hopfield NNs to facilitate the detection of defective dies [51]. The experimental results show that the method works accurately and successfully for detecting defective dies in LED wafers. Fung et al. developed an automated optical inspection system which includes luminance and forward voltage [5]. The proposed approach is based on graphic supervisory control, and was introduced with the concept of LabVIEW software and a programmable logic controller. The method can inspect 40–45 pieces per minute, and the accuracy for luminance inspection is near 100%. Perng et al. focused on the inspection defect of SMD LEDs. An SMD LED comprises a base, LED chip, two pads, and a circuit pattern [6]. Common defects include missing components, incorrect orientations, and surface stains. They presented a system to inspect of defects of SMD LEDs, and obtained 95% accuracy with 0.3 s required per image for online inspection. Template matching has been widely used for the visual inspection of patterned surfaces, and was inspired by the concept by Tsai et al., who proposed a new dissimilarity method based on the optical-flow technique for the inspection [41]. The method can achieve 100% inspection, and can manage the problem of small displacement and product variations of LED wafer dies. In order to effectively recognize the defect of LED chips, Kuo et al. presented a two-stage BPNN model with normalized cross correlation algorithm and K-means clustering [60]. This work focused on five defect types, including fragment chips, scratch marks and remained gold on the pad area, scratch marks on the luminous zone, and missing luminous zone, respectively.

4. Conclusion

AVI, an interdisciplinary research field that combines aspects of manufacturing process analysis, image processing, computer vision, and machine learning, is challenging but vital for quality control and production line automation. With the development of complex and precise electronic products, the semiconductor industry is entering a new stage in the design and manufacturing of VLSI circuits. Automatic inspection techniques have been applied widely in manufacturing processes to ensure product quality and performance. This paper discusses various state-of-the-art visual inspection algorithms and systems that have been applied in the semiconductor manufacturing industry. The vision-based algorithms that were used in previous visual inspection systems can be classified into four major categories: projection methods, filtering-based approaches, learning-based approaches, and hybrid methods. In addition, this paper briefly reviews the applications of related semiconductor products, including wafers, TFT-LCDs, and LEDs. Various product defects and their detection methods were introduced. Defects may be caused by imperfect materials and manufacturing errors of the manufacturing machines, such as pinholes, scratches, erosion, ripples, and mura defects, and also may result from particles or fingerprints left after handling by the operator during manual processes.

In this study, relevant literature was reviewed and divided according to inspection algorithms and semiconductor products. The AVI algorithms used in most previous studies can be categorized into four major types. Traditional AVI systems typically used referential methods, gradually improving in recent years by applying feature-based approaches. Filter-based approaches have been applied widely to extract features from the multi-textured surfaces of precise chips, and to detect the manufacturing defects in regions with inhomogeneous textures that contain complex image information. The literature review of semiconductor products can be a reference for researchers, providing a clear overview of AVI systems, defect types, and applicable products. Much of the inspection system used in LCD manufacturing is designed by applying projection and filter-based methods. Moreover, various machine learning algorithms have been utilized widely to inspect LED surfaces. In current research, hybrid systems that combine multiple techniques is a widely-used strategy to achieve efficient and effective detection during difficult and complex inspection. However, identifying defects in translucent or transparent materials remains a critical and challenging task that relies on manual inspection because defects can only be observed from specific angles or under certain light. Developing an AVI system using multiple light sources, such as point light sources with various angles, intensities, color temperatures, and even circular illumination, may facilitate solving this critical problem.

In addition, an inspection system based on 3D scanning techniques that provide richer, high-definition information should be developed. Reducing the time used is another research issue, because complex visual inspection typically causes a bottleneck in real-time manufacturing lines. Sampling inspection may increase the inspection efficiency, but decrease the production quality dramatically. The precision manufacturing technology used in the semiconductor industry has advanced to 16 nm and will be improved to 14 nm in late 2014. The rapid evolution of manufacturing technologies has lead to increasingly elaborate, smaller chips that have more complicated structures. Several novel image processing and pattern classification techniques have been applied to facilitate precise inspection. For example, super-resolution imaging techniques were developed and used to inspect small regions and complicated chip components. In addition to improved accuracy, time consumption is another critical factor in AVI applications. Parallel computation of multiple pattern recognition and path planning in AVI systems have been proposed to enhance system efficiency for used with semiconductors. In the future, these methods can be expanded to include processing large-scale point cloud data during three-dimensional inspection applications.

In precision engineering and manufacturing, fully automated factories can reduce manufacturing costs and enhance consistent production quality. AVI plays an important role in production automation. However, further research exploring vision-based algorithms and practical applications of AVI is required.

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Szu-Hao Huang was born in Taipei, Taiwan, in 1979. He received the B.E. and Ph.D. degrees in Computer Science from National Tsing Hua University, Hsinchu, Taiwan, in 2001 and 2009, respectively. In 2010, he joined the Department of Quantitative Finance, National Tsing Hua University, as an Adjunct Assistant Professor. Since 2011, he has been with the Department of Industrial Engineering and Engineering Management, National Tsing Hua University, where he was an Assistant Research Fellow and Adjunct Assistant Professor. His current research interests include statistical machine learning, computer vision, automated optical inspection, RGB-D sensing techniques, medical imaging, mobile e-commerce, computational finance, and the development of various interdisciplinary applications. Dr. Huang has authored more than 30 papers published in the related international journals and conferences.

Ying-Cheng Pan was born in Keelung, Taiwan, in 1989. She received the B.S degree in Industrial Engineering and Engineering Management from National Tsing Hua University, Hsinchu, Taiwan, in 2012. She is currently working toward the M.S. degree in National Tsing Hua University. Her research interests lie in computer vision, geometric modeling, ergonomics, and industrial automation.