Activities to Production Support with Visual Information —Technical Development of the Inspection, Measurement, and the Plant-Monitoring—

Sumitomo Chemical Co., Ltd.
Process & Production Technology Center
Atsuhiko Shinoduka
Osamu Hirose
Takashi Suzuki
Masaya Shimizu
Ichiro Washizaki

The image processing technology is widely used for various production fields, for example, object recognition, visual inspection, OK/NG diagnosis and so on. Although the computer technology has advanced rapidly, to make the image processing technique fit for practical use is still extremely difficult issue because the computer does not have comprehensive discretion. The authors have developed total machine vision systems, including the illumination technique, image sensing, image processing, and production improvement techniques, for various production lines. In this paper, the key technology of machine vision is described for each developmental stage. This paper also shows several actual applications involving visual inspection, measurement system, and plant monitoring system.

Introduction

Production activities that depend upon visual inspection by humans are conducted in a great variety of industries. Humans possess an excellent ability to judge the appropriate course of action based upon visual information, thus play an important role in many production activities. However, human workers have serious shortcomings, for example, they can easily become physically or mentally affected by the working environment and significant individual differences in judgment exist among different people. For this reason, it is impossible to completely eliminate human error and it is extremely difficult to maintain stability and objectivity in visual inspection work over long periods of time.[1] Under these circumstances, image processing technology has gained wide application for the purpose of automating many conventional visual identification tasks. In recent years, tremendous advances in computer technology have led to a rapid expansion in the number of applications for image processing. **Table 1** depicts areas in which visual information analysis is often applied.

In actual industrial applications, significant benefits to the automation process cannot be gained merely by converting visual inspection work to image processing. An effective production support mechanism is

Table 1 Application fields of the visual information analysis

Scope	Application fields
Visual inspection	Appearance quality control for foods, medicine, package, electronic parts, automobile parts, film, paper, steel material, etc.
Measurement	Measurement of position, velocity, inclination angle etc. Automatic measurement of visual information
Positioning/Alignment	Industrial robot control, material handling
Geometrical feature recognition	Total inspection of the geometrical features, 3D measurement
Color recognition	Irregular color inspection, Different kind mixing inspection, etc.
Motion measurement	Motion detection, optical flow analysis
Monitoring/Security	Surveillance, detection of unusual plant situation, intruder detection
Research support	Automation of routine research activity such as visual observation, data gathering, data analysis, etc.
Character recognition	Identification of lot-products, Vehicle identification, etc.
Segmentation/Pattern recognition	Label·Inspection of print, Identification of individual (face and fingerprint)
Temperature information	Heat image analysis, Tunnel inner wall flaking off inspection, etc.
Others	Medical treatment, Welfare, Safety device, Entertainment, etc.

required, developed through a system that encompasses a broad range of tasks, from an observation system that helps us to capture information from the image, to methods of applying the visual information itself. This paper explains the various component technologies required to develop a production support system and introduces actual development examples in the following 3 areas: inspection, measurement and plant monitoring.

Overview of Image Processing System that Optimizes Visual Information

In this section, we examine the basic component technologies required to develop an image processing system that optimizes visual information. **Fig. 1** depicts each component technology that supplies data that is effective in improving a particular production process.
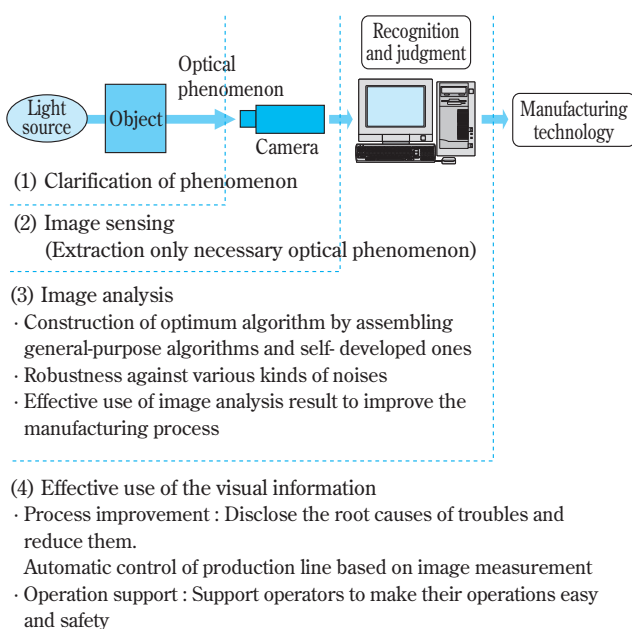

(1) Clarification of phenomenon

(2) Image sensing
(Extraction only necessary optical phenomenon)

(3) Image analysis
· Construction of optimum algorithm by assembling general-purpose algorithms and self- developed ones
· Robustness against various kinds of noises
· Effective use of image analysis result to improve the manufacturing process

(4) Effective use of the visual information
· Process improvement : Disclose the root causes of troubles and reduce them.
Automatic control of production line based on image measurement
· Operation support : Support operators to make their operations easy and safety

Fig. 1 Effective data supplying to manufacturing process

(1) Elucidation of Optical Phenomena

In an image processing system, the most important factor is to utilize imaging technology that provides a method for capturing images that can be readily inspected and processed. In other words, the images captured must include extractable visual information that is required for the production process. In general, it is difficult to capture the requisite visual information merely by using a camera. For this reason, an optimal observation system most suited to each optical phe-

nomenon must be created through the elucidation of the optical phenomenon caused by the interaction of the object and the light source.

(2) Capturing Images

Table 2 depicts the important base elements required for capturing an image. Among all these elements, items numbered 1 ~ 3 are the base elements relating to the lighting system. The following elements are important in the creation of a lighting system: 1. elucidation of an information carrier suited to the particular object (visible light, infrared light, ultraviolet light, temperature distribution, etc.); 2. characteristics of the light, as affected by the object (reflection, transmission, diffusion, diffraction, etc.); 3. observable intensity of the light. As well, items numbered 4 ~ 6 are the most important base elements relating to the imaging system. The following elements are important in selecting the most suitable camera and lenses for imaging: 4. format of information acquisition; 5. frame rate; and 6. view. The appropriateness of the selection of these base elements greatly affects the overall imaging performance, as well as the image inspection and measurement performance. Therefore, it is crucial that the observation system be created by selecting the optimal base elements in strict accordance with the desired purpose.[2]

Table 2 The base elements for image construction

#	Base element	Contents
1	Information carrier	Visible light, Infrared or Ultraviolet light, Temperature distribution, etc.
2	Characteristics of the light	Reflection, Transmission, Diffusion, Scattering, Luminescence, Absorption, Straight light, Refraction, Diffraction, Interference, Polarized light, Wavelength, Chromaticity, etc.
3	Intensity of the light	(Compared with the dynamic range of camera) Over-range ~ optimum range ~ under-flow
4	Information acquisition form	1D, 2D, 3D data, Protein structure, Inside information, etc.
5	Frame rate	Still image, NTSC, Double speed (60FPS), High-speed camera, etc.
6	View	Microscope image, Close-up image, Standard, Wide angle image, Long shot image, etc.

(3) Image Processing

The image processing portion of the system extracts

visual characteristics from the captured image, recognizes and identifies them, then outputs the results in a form of a signal. The following two functions are the primary functions required for image processing: The first requirement is to have a stable data extraction function, meaning that the system must possess a robust algorithm with high noise rejection and have judgment capabilities equivalent to that of a human visual inspection. Another requirement is to have an effective function for feeding data to the production process. In order to achieve these goals, it is necessary to obtain knowledge about the production process, as well as to handle the characteristics of the image.

(4) Optimization of Sensing Data

It is important to create a system that facilitates the improvement of the production process, such as stabilizing the production line and providing support to the operators, based upon the data supplied.

Examples of Image Processing Systems that Optimize Visual Information

1. Automation of Defect Inspection

(1) Background Information for Chemical Product Inspection and Defect Characteristics

Fig. 2 depicts the various materials that comprise a liquid crystal display, such as the polarizing film, light guide sheet and diffusion sheet. As the precision and brightness of these display devices have increased significantly in recent years, a higher quality appearance is now demanded from these materials as well. The level of defects that must be detected has reached the limits of human visual inspection, thus making automated inspection inevitable. **Fig. 3** depicts some typical
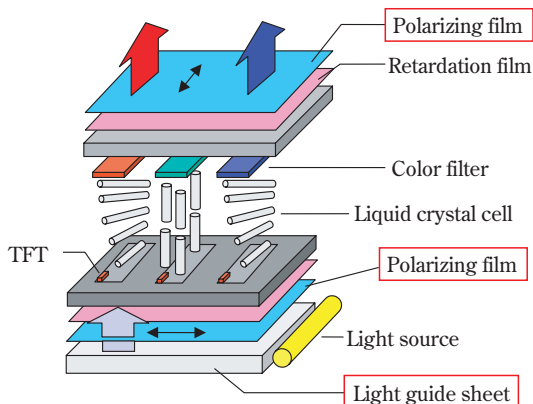
Fig. 2　Structure of LCD display

	Defect classification	Location	Defect	Suitable lighting system
Polarizing film	Dimple, Stain, Scratch, Bubble, Particle	Surface	Stain Scratch	(Diffused) Reflected light
			Dimple	Diffused transmitted light
		Inside	Bubble Particle	Transmitted light
Diffusion sheet	Pit mark, Bank mark	Surface	Bank mark Pit mark (Diffusion sheet)	(Diffused) Reflected light
Light guide sheet	Black spot		Bank mark Pit mark (Light guide sheet)	Diffused transmitted light
		Inside	Black spot	Transmitted light

Fig. 3　Characteristics of defects on the optical sheets

characteristics of defects. There are a variety of different types of defects and they can occur in many different locations. The observation conditions suitable for defect detection vary depending upon the type of defect. In general, transmitted light is used to detect coloration defects (stains) and reflected light is used to detect object surface unevenness. Furthermore, there is also a method of detecting the light diffused by defects lying under the dark field areas. The greater the number of different defect types present, the greater will be the number of observation methods required.

(2) Defect Observation Method Utilizing Polarized Light

This section introduces an observation method that utilizes polarized light. It is an example of a means of identifying a variety of defect observations through the use of a fixed optical system.

Polarizing film has the property of only transmitting light polarized in a specific direction. In our example, depicted in **Fig. 4** (a), the transmission axis of a second polarizing film is positioned orthogonally to that of the subject (primary) polarizing film (Crossed Nicols Optical System), allowing the observation of images on a dark field, where light is blocked from entering the observation region. If any defect, such as a foreign object, is present between the two polarizing films, the light striking the defect will be diffused, disturbing the light's polarization and producing a light component

that is transmitted through the second polarizing film. This transmitted light component is then observed as a bright point on the dark field image, indicating a defect. However, this method does not permit the detection of defects located on the lower side of the subject polarizing film, as they present dark images themselves and thus would not be visible within the dark field image. Therefore, as depicted in Fig. 4 (b), the optical system must be carefully adjusted in a manner such that a small amount of transmitted light can still be observed in the normal region. This adjustment involves angling the second polarizing film from the fully Crossed Nicols state by a small amount (in this case, 5 degrees), so that the abovementioned effects of polarized light are not lost. This change allows for the detection of light-blocking defects that are located on the lower side of the subject polarizing film.[3]

As indicated by this example, in order for automated inspection systems to be put into practical usage, it is extremely important to detect as many defects as possible using a small number of optical systems.

Defect observation images

(a) Crossed Nicols optical system (b) 5 degree-opened system
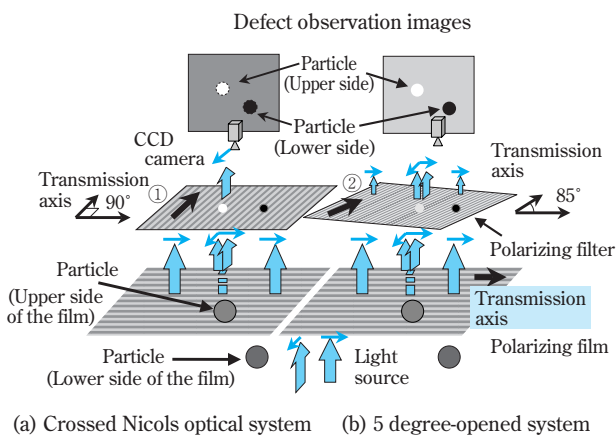
Each planate arrow shows transmitted light, which plane means electric field direction.
Electric field direction of each light is also indicated by linear arrow in front of the planate one.

Fig. 4 Observation method by using Crossed Nicols optical system

(3) Defect Detection / Identification Algorithms
(i) Defect Detection

It is not an easy task to immediately extract all defect information from an observed image. In most cases, defects are buried within a variety of noise signals, with only minor differences in brightness between defect regions and normal regions (low signal to noise ratio). Therefore, image processing suited to the particular

object being detected must usually be performed.

Generally, observed images contain uneven levels of brightness, which has low spatial frequency. This phenomenon is usually referred to as "shading." Shading is often caused by uneven lighting or reflections from shadows of obstructions. A method often utilized for eliminating shading is called finite difference calculus. Also, since shading often changes with the passing of time, the dynamics of the background image must often be adjusted, as well.

Furthermore, images may also contain high frequency, low amplitude noise. This kind of noise can be eliminated by performing an image processing method known as "spatial filtering" (weighted moving average). In addition, this method also utilizes an operator (weighting matrix) that emphasizes local signals, while simultaneously smoothing out noise across a particular area (referred to as the weighting matrix). Users may also find it effective to create and utilize a variety of different operators, in accordance with the particular objects being detected.

(ii) Defect Identification

In the production process, it is extremely important to specify the nature of the particular defect that has been identified. Therefore, a special type of algorithm is required to categorize the type of defect as inspection data. In this system, the defect identification procedures are as follows: at first, defects are roughly classified based upon their basic image characteristics, such as brightness, size and moment; next, pattern identification of the defect image is conducted whenever necessary to detect the occurrence of the specific defect; lastly, the conditions surrounding known defects that have occurred previously are continually analyzed to detect defect concentrations and periodic defects. This defect data is considered to be effective information for use when managing the manufacturing process.

(4) Supplying Inspection Data to the Production Process

There are 2 forms of inspection data that may be used: non-visible data and visible data.

Non-visible information is shared inspection information that is available via computer. It is used in production planning for the lower production line stream and is used as feedback for the upper production line stream. In this case, although the data does not have to be visible, it is crucial that the information is shared on

a real-time basis.

On the other hand, visible information is utilized in a manner such that the inspection data is made visible for workers from that point forward in the production line. More specifically, the key to this process, as described in the following section, is the use of marker technology for defect regions.

(5) Marker Technology

(i) Marking Procedures

The most popular marking methods utilize the inkjet, labeling, felt pen or stamping. The following factors must be taken into account when choosing a marking method: workpiece characteristics (water repellence, permeability, color, etc.); post-processing method (cutting, coiling); effects upon non-defect regions (transfers, etc.); cost (primary costs, operating costs); and maintenance.

(ii) Marking Methods

Fig. 5 depicts the marking methods used for a series of workpieces.

(a) Edge of Workpiece Marking
———————————— Fixed Position Marker
(b) Defect Marking ——————— Traversal Marker
(c) Zone Division Marking — Fixed Position Marker
(Marker Array)

(a) Fixed position marker

(b) Traversal marker

(c) Marker array
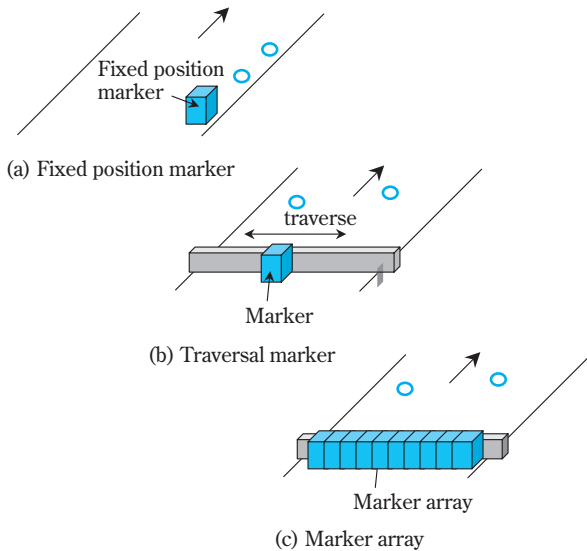
Fig. 5　Marker type selection

Although (a) Edge of Workpiece Marking is very simple, it does not provide a direct indication of the defect region. Therefore, this method is not of utility for production line operating staff. If the defect region

is directly indicated, this information will be useful further on in the production process, thus allowing for a direct assessment of the defect detection rate. Thus, the use of (b) Defect Marking, or (c) Zone Division Marking, would be ideal, if possible.

With (b) Defect Marking, a marker is fixed in position (traverse) directly at the defect region. This method only requires one marker. However, the possibility exists that this fixed marker may not cover all possible defects when multiple defects occur over a narrow range. In this case, some defects will not be marked (marker miss). In contrast, with (c) Zone Division Marking, several markers are aligned at similar intervals and each individual marker is controlled independently. Therefore, although this method does require many markers, "marker miss" will never occur. The most suitable method should be selected based upon the true "marker miss" rate for the actual production line.

(6) Machine Vision and Human Vision

The processing of images using a TV camera (machine vision) has many advantages not possessed by a visual inspection using human eyes (human vision). **Fig. 6** depicts the relationship between defect size and detection rate. It has been discovered that the detection limit for human visual inspections is approximately 0.1 mm^2.[4] If defects are smaller than this size, the detection rate using visual inspection will decrease significantly. However, machine vision is capable of detecting defects of far smaller sizes. Furthermore, there are many advantages with machine vision, such as having no individual differences in equipment, high repeat accuracy and being capable of continuous operation over long periods of time. However, on the other hand, machine vision lacks the flex-
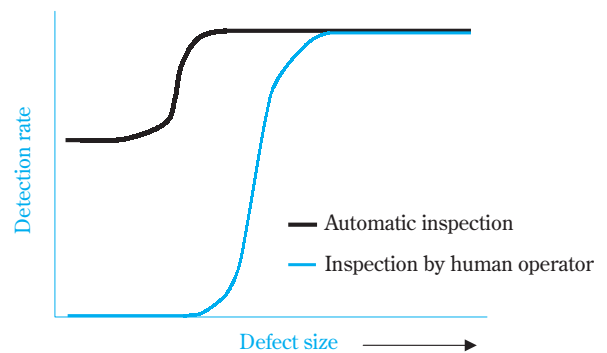

Fig. 6　Variations of detection rate with defect size

ibility and high ability for judgment possessed by humans (especially its robustness against diverse types of noise).

Based on these factors, it is difficult to completely replace human visual inspection with machine vision, at the present time. In the process of inspection automation, it is inevitable for systems to be created that combine the best features from both human vision and machine vision, which together compensate for the shortcomings inherent in each type of vision. More specifically, the following system is now in popular usage: a quantitative inspection for minute defects is performed using machine vision and overall judgment is performed by human inspectors.

(7) Challenges in Putting the System into Practical Use
(i) Decreasing False Reports

When attempting to improve defect detection sensitivity, the number of false reports (i.e., an error in which a normal region is detected as a defect region) will increase. There are two primary causes of false reports. One is noise and the other is permissible scratching. For example, extremely slight scratches on a protective film that will later be removed and discarded, are considered permissible. In order to decrease such false reports, we have been attempting to improve defect recognition ability by analyzing a quantity of image characteristics for both defect reports and false reports, as well as creating an observation system in which noises have been reduced.

(ii) Stabilizing the Observation System

For the inspection of very minute defects with sizes smaller than the lower limit for visual inspection, the camera must have extremely fine resolution of better than 10μm. This means that the depth of field is extremely shallow, therefore, the camera's working distance (distance from the camera lens to the workpiece) has very small allowable tolerances for fluctuation. However, in reality, when conveying a film-like type of workpiece, the workpiece is usually subjected to some degree of up-and-down vibratory motion. This vibration causes the camera focus to blur, thus reducing detection sensitivity. **Fig. 7** depicts signal-to-noise ratios (S/N ratios) for the same defect sample over various camera working distances. Since this defect sample is extremely minute, an adequate S/N ratio cannot be obtained unless a resolution of better than 50μm / pixel is used. However, if a greater resolution is used, the camera working distance must be reduced or the

S/N ratio will be too low. In order to maintain a high S/N ratio, a more stable film conveying system is required. Thus, it is important that the manufacturing system be designed with consideration for the quality of inspection performance.
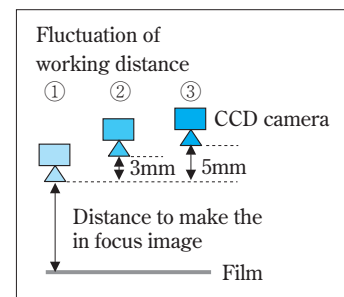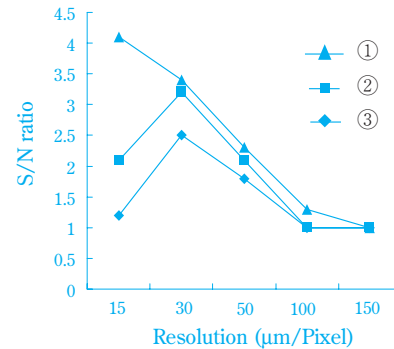
In this case, over 100μm/pixel resolution is not practical because of the low S/N ratio. At the same time, higher resolution (under 30μm/pixel) is also undesirable because the S/N ratio decreases drastically with working distance of camera. Therefore, practical camera resolution range is restricted to around 50μm/pixel. It is necessary to reduce the vibratory motion of the film to make it practical with higher resolution.

Fig. 7 Variations of the signal to noise ratio involving the same defect sample with camera working distance and resolution

2. Example of Measurement Automation
(1) The Concept Behind Measurement Automation

In general, for image measurement, the most important elemental technology must first be identified for each individual need, then an observation system must be designed that is well-suited to the technology. This section introduces an example showing the "quantitization of function evaluation" as an elemental technology, where previously only human senses had been relied upon.
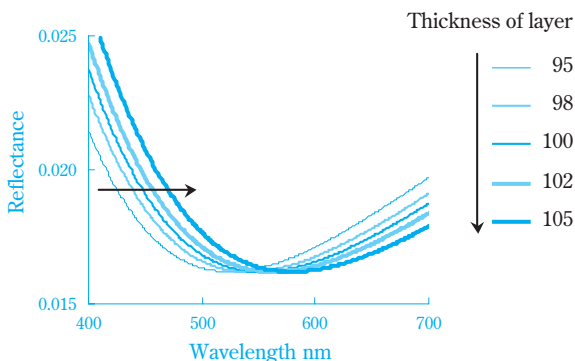
(2) Quantitization Technology for Function Evaluation
— Instrumentation for Detecting Product Surface Color Shading Defects —
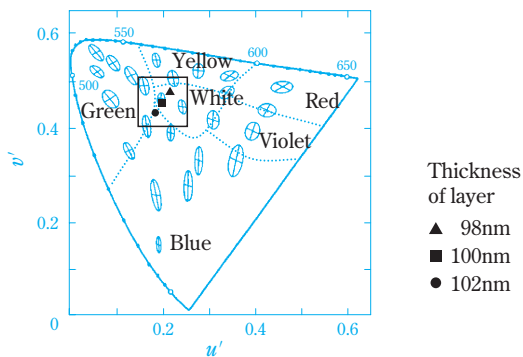(i) Challenges in Inspecting Color Shading Defects

There are many products for which color differences can be a serious problem in terms of appearance, such as for display materials and automobile bodies. It is relatively easy to express color differences quantitatively, as a variety of colorimetric systems have been standardized for the expression of colors. However, in reality, it is extremely difficult to perform accurate color shading defects inspections using only instrumentation. In many cases, this process must rely solely upon human visual inspection. The reason for this dependence is that the effects of color differences upon the human senses (not the physical amount, but the "psychological amount") are extremely difficult to express quantitatively.

(ii) Defect Properties of Anti-Reflective Film

This section describes the quantitative evaluation of color shading defects in anti-reflective film. Anti-reflective film is composed of several thin layers of film (the thickness of each film layer is usually 50-150nm). The presence of several thin film layers results in low spectral reflectance at the wavelengths for visible light. **Fig. 8** depicts variations of spectral reflectance and chro-

(a) Variations of spectral reflectance

(b) Valuation of visibility of color difference by using MacAdam's ellipsoid

Fig. 8 Variations of spectral reflectance and chromaticity with thickness of layer involving the single layered anti-reflection

maticity on a single layered anti-reflective film made by forming a thin film (with thickness of 100±5nm) onto a substrate with a refractive index of 1.49. It can be observed that the spectral reflectance curve shifts in the direction of the wavelength axis, in accordance with changes in the film thickness, thus indicating changes in the chromaticity. The changes in chromaticity are greater than with the MacAdam's ellipsoid[5] shown when using the same scale of magnification, thus indicating that these changes can be distinguished accurately by the human eye.[6]

However, with actual defect measurement, no correlation is observed between the difference in chromaticity and the level of color shading defect. In some cases, although a color difference has been clearly identified, it can still be allowed. On the contrary, in other cases, although only very slight color differences are present, if there are many such small differences, this will be considered a defect. For this reason, measurements must be performed on the "psychological amount" received from the overall visual field, not merely from an individual color difference.

(iii) Attempting to Quantitize Function Evaluation

It has been discovered that humans possess the following vision characteristics: due to an effect from the lateral inhibition[7] of the optic nerves, humans subconsciously pay particular attention to changes in color and color intensity; and if the eye's fixation point jumps rapidly (saccade)[8] within the field of vision, then vision processing will temporarily pause during the movement. From these facts, it can be assumed that the frequency of inhibition of human vision processing caused by intense attention to defects, will greatly affect the "psychological amount." Therefore, we performed an experiment that focused upon the frequency distribution of the chromaticity observed in a single test piece. The frequency distribution of the color difference was measured for each of the 28 test pieces used. In addition, the defect evaluation values obtained by humans were digitized using the comparative appraisal method. **Fig. 9** depicts the results of this experiment. The frequency distribution curves observed in this experiment can be described as follows: a thin and sharp unimodal curve was seen for test pieces that evaluated as having a small defect (this tendency became greater as the color difference decreased); and a lower and less steep curve was seen for test pieces that evaluated as having a large color difference (this tendency became greater as the color dif-

ference increased). As a result, we observe that there is a strong correlation between the frequency distribution curve and the values obtained by the comparison appraisal method. Using this correlation, various gradations for color shading defects can be defined by approximating a threshold curve, as indicated by the dotted line in Fig. 9.
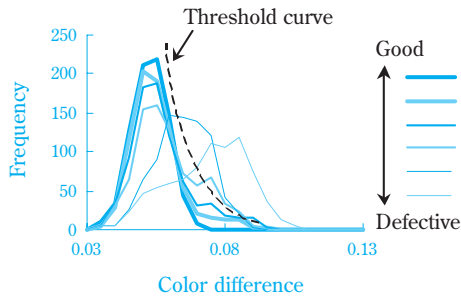

Fig. 9 Frequency distribution of color difference

3. Example of Plant Monitoring Automation

(1) Objectives of Plant Monitoring

An Intelligent Production Center (IPC) has been established within the Niihama Primary Manufacturing Department of the Ehime Chemical Factory. The IPC is a system that integrates 9 separate operations instrumentation (control) rooms, each of which had previously been located in a different area of the plant, into a single room. The IPC facilitates the full integration of plant operations from a single location and thus results in increased distances between the actual production sites and the control center. Therefore, an automated monitoring system has been developed that employs CCD cameras and image processing technology to detect any abnormal plant operations at an early stage. This system also helps to reduce the burden of continual plant operations monitoring for production line workers.

(2) Plant Monitoring Using Image Processing Technology

Table 3 depicts the monitoring objects for which automated monitoring is required. Although smoke detectors and flame sensors are commercially available, these products can only detect smoke particles and heat in direct proximity, thus must be installed in the vicinity of the objects being monitored. In a huge chemical plant, the installation and monitoring of myriad sensors is very difficult, especially when the costs of installation and maintenance are considered. In

addition, it is not possible to install sensors within certain plants. In contrast, a single camera can monitor a wide area and its range can even be enhanced with rotational and long-distance monitoring capabilities. Moreover, in some cases, visual inspection is a legal obligation, such as the visual inspection requirements for water levels within boilers. Certain other cases make it unfeasible for inspections other than visual inspections to be used, such as the examination of powdered or granular matter. In these cases, the development of automated monitoring systems that possess detection capabilities equivalent to those of human visual inspection will result in earlier detection of abnormal operations and defects, as well as reducing the burden on plant staff.

Table 3 Examples of the application fields that require the plant monitoring system

Scope	Monitoring object	Detection items
security	whole chemical plant	fire (flame & smoke)
		leakage of gases or chemicals
production control	Gauge products or materials	water level in a boiler drum
		properties of powder or grains
		liquid drops or spray

(3) Specific Examples of Plant Monitoring

Plant monitoring is used in the automatic detection of phenomena that would be determined as "abnormal" by human visual standards, from specific image data. The most important aspect of a plant monitoring system is the method used to determine the presence of abnormalities.

Several examples of automated monitoring systems that employ image processing technology are described below.

(i) Smoke Detection

Fig. 10 depicts an algorithm for sensing smoke. This algorithm is composed of 3 parts: (a) preprocessing, (b) identification of the smoke image, and (c) a decision. The details of each part are explained below.

(a) Preprocessing

The preprocessing procedures performed prior to obtaining a smoke image, are as follows: ① image grab (image capture); ② subtraction (creation of a difference image); and ③ accumulation (accumulation of subtraction images). **Fig. 11** depicts the detailed operation of the preprocessing procedures. A unique characteristic of smoke is its movement as it floats within
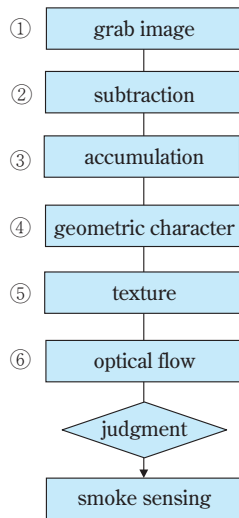
① grab image

② subtraction

③ accumulation

④ geometric character

⑤ texture

⑥ optical flow

judgment

smoke sensing

Fig. 10   Algorithm for smoke sensing

Image ①

subtraction

|②—①|

Image ②

accumulation
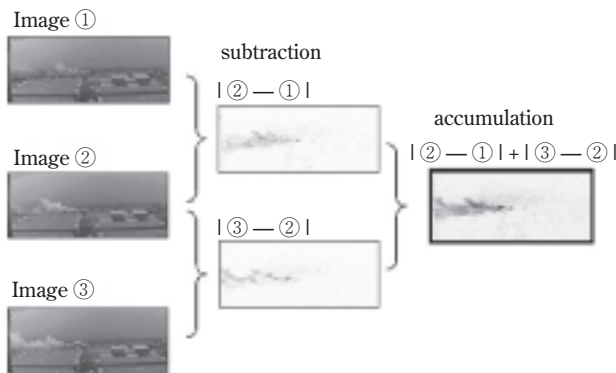
|②—①|+|③—②|

|③—②|

Image ③

Fig. 11   Extracted image of drifting smoke

the air. Even if finite subtraction images are created in order to capture the movement of smoke (motion change), the changes that appear from image to image are extremely minor, as smoke typically moves quite slowly. However, by accumulating several finite subtraction images a final image can eventually be constructed that clearly depicts the actual changes occurring over multiple images.

(b) Identification of Smoke within the Image

The following procedures are performed to identify if the apparent smoke within the preprocessed image is actually real smoke: ④identification by extraction of shape characteristics (geometric character); ⑤identification by analysis of texture (textural analysis); and ⑥ identification via optical flow (optical flow).

As indicated in **Fig. 12**, identification is performed using a region of smoke obtained from the shape factor extraction process. The following factors are utilized to define shape:
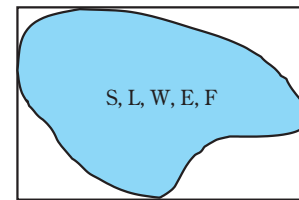

S, L, W, E, F

Fig. 12   Shape factor

S : Area

L : Circumference

E : Roundness (= $4\pi S/L^2$)

F : Complexity (L^2/S)

W: Fillet Share

(Ratio of shape area occupied, to area of smallest rectangle that could surround the shape.)

In textural analysis, as depicted in **Fig. 13**, identification is performed using the 3 methods described below, through the changes in the concentration difference (brightness information) within the smoke region.
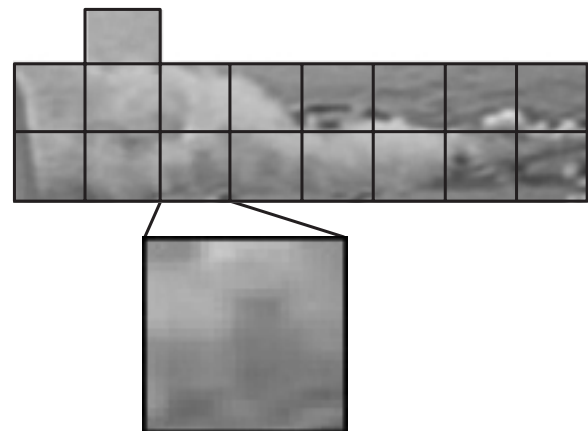

Fig. 13   Texture in smoke region

• Pattern characteristic extraction
• Textural analysis using concentration histogram
• Textural analysis using simultaneous occurrence matrix

In the optical flow method, the movement of the object (changes in both direction and in quantity) is characterized and then identified. Smoke flows in an extremely complex manner in small areas. However, as shown in **Fig. 14**, the expression of this motion as areas of flow change for each particular region allows the overall motion to be captured.

(c) Decisions

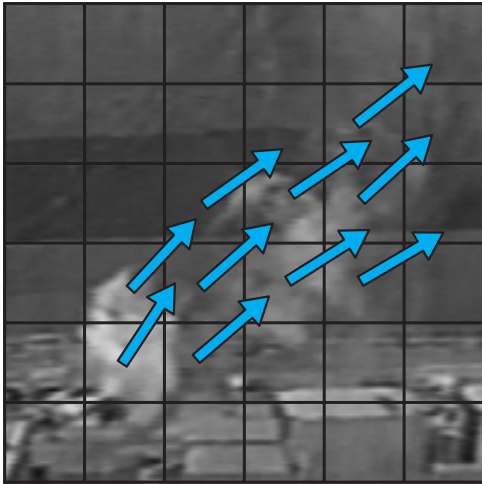Through a comprehensive assessment of the results

Fig. 14 Motion information of smoke by optical-flow-method

obtained from the above identification methods, external disturbances (such as climate changes, moving objects (humans, vehicles, etc.) and reflections from light fixtures) can be eliminated, thus improving the accuracy of smoke detection.

(4) Oil-Water Interface Measurement Using Moving Images[9]

① Actual Conditions at the Surface Interface

In many cases, the liquid surface of a tank or the oil-water boundary within an oil / water separation tank, will require constant monitoring and control. With respect to existing technologies, a variety of liquid level indicators and interface gauges, such as float gauges, impedance gauges, differential pressure gauges and chemical indicators, are currently available on the market. However, the proper application of these existing technologies requires relative stability of the following properties: specific gravity, which is the principal measurement needed, as well as other properties, such as impedance. In reality, many production sites cannot utilize standard commercial systems due to the following conditions: the properties to be measured are not constant; and the difference between the two types of liquids is extremely minor.

② Problems in Interface Measurement Using Images

Fig. 15 depicts an example of images from the inside of an oil-water separation tank, which were taken through the sight glass. The images contain a variety of noise, at levels that are obviously higher than that of the interface image data to be extracted. In most cases, it is impossible to extract the interface image data from these images using standard image processing tech-

nology. In addition, these images are only examples - in actual situations, image brightness and noise caused by reflections will change as time goes by, depending upon the time of image capture (during day or night), the weather and the surrounding conditions. We therefore needed to establish a robust measurement technology that could respond to such changes.
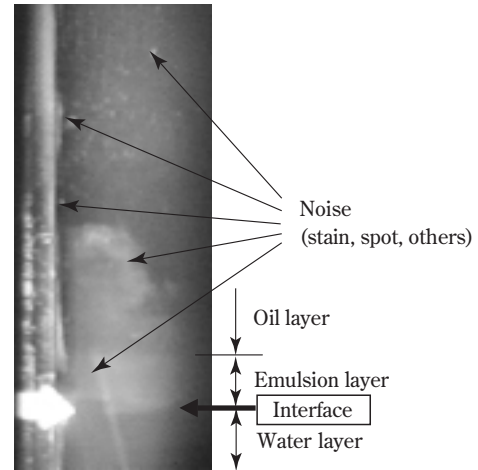

Fig. 15 Observation of a sight glass on the oily water separating tank

③ Interface Data Extraction Algorithm Using Moving Images

Fig. 16 depicts the procedures used in processing these images. Diagram (b) depicts the finite time difference between (a) the 2 original image frames. Next, the moving extracted image (d) is obtained by automatically determining the threshold value from the brightness distribution histogram (c), using statistical techniques. This value is then converted into binary. From this image, the direction of interface movement (whether the interface is rising or falling) is then determined using pattern recognition and the interface position is specified with an arrow, as shown in diagram (e).

④ Efforts to Achieve 100% Reliability

In general, fluid image extraction technology using finite frame differences is utilized in the areas of intruder surveillance and traffic volume measurement. In such standard applications, the correct information must be output only when some motion has occurred. However, in this particular example, the correct interface position data must be output, regardless of the occurrence of motion.

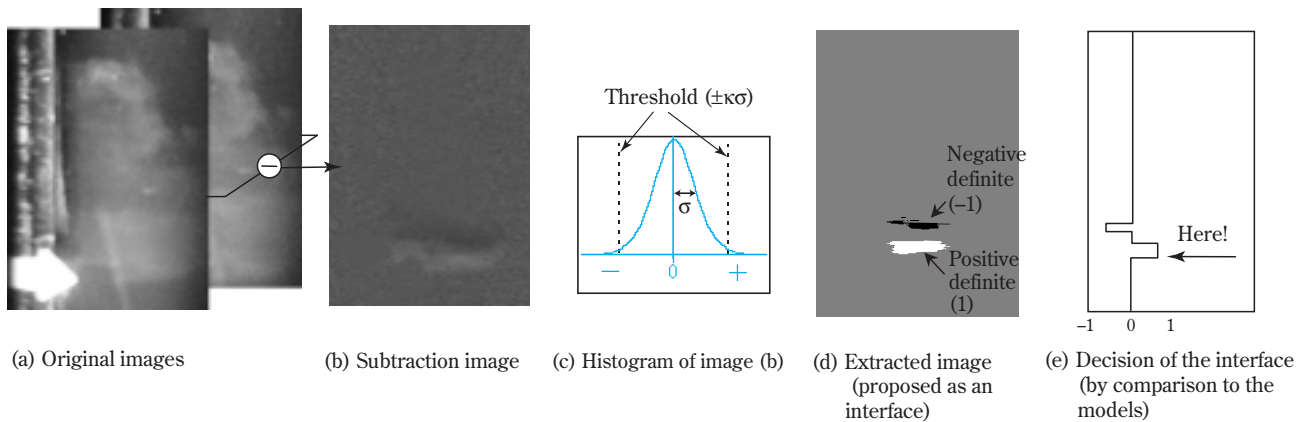(i) Majority Decision Method Using Finite Differences from 3 Individual Images

      10

(a) Original images   (b) Subtraction image   (c) Histogram of image (b)   (d) Extracted image (proposed as an interface)   (e) Decision of the interface (by comparison to the models)

Fig. 16   Examples of image processing

The strong possibility exists that no differences may be visible in the interface positions between 2 images. Therefore, image analysis was conducted for each of the following 3 images: an image captured a few seconds prior; the image having the lowest interface position among all 3 images; and the image having the highest interface position among all 3 images. We decided that the usage criteria for each measured value would require that more than two measurement results be of that same value.

(ii) Determining the Presence of an Interface at the Extracted Position

We employed a neural network to determine whether the image extracted as an interface was the true interface. We eventually achieved consistent decision-making by allowing the network to learn from "teaching data" comprised of 70 different images having interfaces and 50 different images without interfaces.

Conclusion

For the inspection of electronic display panel components, it has been said that no technology exists that yet surpasses the capabilities of human visual inspection. However, the required inspection accuracy is now about to exceed the limits of human visual inspection. For this reason, it is necessary to create automated inspection systems that possess great precision, high speed and advanced decision-making technology, all of which must exceed the capabilities of human visual inspection. In addition, the technology used to supply effective data from the image processing system to the actual production line, as introduced in the sections describing measurement & monitoring technologies, must continue to evolve. As described by the proverb

"The picture is worth a thousand words," humans conduct production activities by obtaining myriad information using their visual inspection abilities. From this point forward, we would like to continue the proactive expansion of areas in which visual information processing can be applied.

REFERENCES

1) Y.Nitta, "User Guide Series / Practicable Guide for Installation of Video Sensors", 1st edition, Denki Shoin, (1988), p.58 (in Japanese)

2) H.Tsuchiya, "Image Processing and Application Series 2 /Measurement with Image Processing (Imaging and Analysis)", 1st edition, Shokodo, (1994), p.4 (in Japanese)

3) Sumitomo Chemical, Published patent 2001–349839 (2001) (in Japanese)

4) M.Ando, Y.Inagaki, Automatic Inspection System for Printed Patterns on Electric Circuit Board, Fujitsu, **35** (6), 721 (1984) (in Japanese)

5) D.L.MacAdam, Visual sensitivies to color differences in daylight, J. Opt. Soc. Am, **32** (5), 247 (1942)

6) O.Hirose, M.Tanaka and A.Ishii, Quantitavive Inspection of Color Shading Defects on the Anti-Reflection Coating (2nd Report) –Validation of Defect Prominent and Perceptual Threshold–, J.Japan Soc. Prec. Eng., **70** (3), 359 (2004) (in Japanese)

7) T.Matsuda, "Base of Perceptual Psychology", 1st edition, Baifukan, (2000), p.23 (in Japanese)

8) B.L.Zuber, Saccadic suppression, Quartery progress report, I.T., **75**, 190 (1964)

9) O.Hirose, I.Washizaki and T.Nakai, Measurement

at Two-solution Interface with Image Processing, J.Japan Soc. Prec. Eng., **67** (8), 1266 (2001) (in Japanese)

PROFILE

Atsuhiko SHINODUKA

Sumitomo Chemical Co., Ltd.
Process & Production Technology Center
Senior Research Associate

Masaya SHIMIZU

Sumitomo Chemical Co., Ltd.
Process & Production Technology Center
Research Associate
Ph. D.

Osamu HIROSE

Sumitomo Chemical Co., Ltd.
Process & Production Technology Center
Research Associate
Ph. D.

Ichiro WASHIZAKI

Sumitomo Chemical Co., Ltd.
Process & Production Technology Center
Senior Research Associate

Takashi SUZUKI

Sumitomo Chemical Co., Ltd.
Process & Production Technology Center