High-resolution optical inspection system for fast detection and classification of surface defects

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ABSTRACT
A high-resolution automated optical inspection (AOI) system based on parallel computing is developed to achieve fast inspection and classification of surface defects. To perform fast inspection, the AOI apparatus is connected to a central computer which executes image processing instructions in a graphical processing unit. Defect classification is simultaneously implemented with Hu’s moment invariants and back propagation neural (BPN) approach. Experiments on touch panel glass show that using 100 training samples and 1000 cycle iterations in BPN, the accurate classification of surface defects for a $350 \times 350$ pixels image can be completed in less than 0.1 ms. Moreover, the inspection of a $43 \text{ mm} \times 229 \text{ mm}$ sample that yields an 800 megapixel raw data can be completed remarkably fast in less than 3 s. Thus, the AOI system is capable of performing fast, reliable, and fully integrated inspection and classification equipment for in-line measurements.

KEYWORDS
Back propagation neural; defect classification; defect inspection; image moment invariants; parallel computing

1. Introduction
With the development of handheld devices, optical inspection has been widely used in defect detection.[1–3] In production lines, automated optical inspection (AOI) systems are used either as sorting machine for process evaluation or as detection equipment for quality control. These two operations are usually independent, where the detection system is typically disconnected from the sorting apparatus or a manual visual test station. Most of the inspection systems were dedicated to finding surface flaws,[4,5] and leaving out the defect classification and sorting for manual inspection.

To rectify production issues promptly and close to real time, a unified detection and process assessment equipment becomes necessary. Obviously, an automated defect-type classification catalogue that integrated to AOI equipment can replace manual visual inspection for improvement of any manufacturing operation. However, one of the potential bottlenecks for such system is the means to deal with large data. Therefore, the use of parallel computing architecture that deviates from traditional multi-CPU platform for fast data computation is deemed more practical.

Recently, Chang et al.[6] developed an AOI technology based on a high-resolution linear charge-coupled device (CCD) to implement surface defect inspection over wide area samples. At 3.5 µm per pixel resolution of the linear CCD, there were at least 147 megapixel image data per second transmitted from a host CPU to a graphical processing unit (GPU) device for image...
processing. The 2D inspection system accurately detects microscopic flaws on touch panel glasses in less than 1 s. The computations were sufficiently fast compared to CPU-based processing.

The present work improves on the AOI apparatus reported in Chang et al.\cite{6} in terms of simultaneous execution of defect detection and classification. The detection is based on the principle that the presence of defects on the specimen will scatter light toward the detection plane of a linear CCD camera. Therefore, a high-resolution defect map of the specimen can be reconstructed by scanning the entire length of a sample. From this map, surface features that are unique to the specimen can be identified and those that are defects in nature can be classified. Standard techniques in digital image processing\cite{7} will be utilized and the executions are implemented on a GPU device using compute unified device architecture (CUDA) kernels. Auxiliary noise filtering algorithm is included to make the inspection system robust for different types of surfaces, particularly specimen that can yield very poor contrast. Recently, deep machine learning technique has also been introduced into the field of optical inspection systems.\cite{8,9} Although the accuracy of defect detection can be greatly improved by learning of defect characteristics, the number of training samples is very large and the training time is very long. In addition, the current target is still focused on defect detection and less applied to defect classification. The classification of defects in this study is implemented by comparing a defect’s luminance characteristics to a target pixel value using the Hu’s moment invariants.\cite{10,11} Characteristic normalization values and the back propagation neural (BPN) model are implemented to train the AOI classification algorithm to recognize defect characteristics. Classification of bubble features and scratch defects using a small number of training samples and few iteration cycles are presented and shown sufficient to perform fast and reliable inspection even deal with an image under very poor contrast. Micron-sized features on the touch glass panel with approximately 800 megapixel raw data have been discriminated within a total detection and processing durations of about 3 s. The presented approach based on image moment invariants with the detection utilizing a linear CCD has shown significant and reliable performance in both speed and resolution.

2. Optical inspection framework

The typical framework of an optical inspection module integrated to a computer network for in-line inspection is based on a system of cluster computer which can process large volume of data from a single AOI machine or multiple systems and then transmitted the results to a common server. In this study, the construction of AOI equipment is shown in Figure 1, where both the imaging module and specimen stage are controlled automatically by a software package custom developed for the AOI system for image processing and hardware controllers.\cite{6} The imaging module consists of 12,288 pixel-line CCD camera (Basler raL12288-66 km) with 3.5 µm per pixel resolution and lens assembly. The illumination is provided by an light emitting diode (LED) array positioned a few centimeters above the specimen stage. The actual spacing used between the light source and target surface can be adjusted according to the surface characteristics of the specimen. Since the light reflected from the transparent sample is very weak, 10 mm was selected to inspect the surface of the touch panel

### Nomenclature

- **AOI**: Automated optical inspection
- **BPN**: Back propagation neural
- **CCD**: Charge-coupled device
- **CPU**: Central processing unit
- **CUDA**: Compute unified device architecture
- **GPU**: Graphics processing unit
- **I(x, y)**: Intensity distribution of 2D image
- **LED**: Light emitting diode
- **MSE**: Mean square error
- **M_{pq}**: Raw moment of order \((p + q)\) of 2D image
- **W**: Weight in neural networks
- **Φ\_i**: Hu’s moment invariants
- **α**: Momentum in neural networks
- **η**: Learning rate in neural networks
- **θ**: Bias in neural networks
- **μ_{pq}**: Central moments of order \((p + q)\) of 2D image
Light scattered from the surface of the specimen due to surface defects is collected by the line CCD. If the surface is perfectly smooth, which is an indicator of a flawless sample, the recorded image is mostly dark. Conversely, the appearance of bright zones over a dark background on the image will suggest the presence of defects. Image data collected by the camera are transmitted to a local CPU. Instead of using multiple CPUs to perform simultaneous computing, the developed inspection software uses a GPU device. Hence, both the inspection and classification tasks can then be implemented on a single computer.

Parameter settings such as capture rate of the CCD, speed of the motorized stage, and acquisition time are user-based commands which can be selected depending on the type of specimen to be tested. The inspection line rate of the CCD in this study was 10 kHz. After the linear CCD and motorized stage are initialized, the image data are first stored on a local CPU. Standard data processing commands are assigned as CUDA kernel functions to a GPU. The kernels are performed as pixelwise operations on a designated block of CUDA threads. Initially, the raw data are copied from the CPU’s main memory to the GPU’s global memory through message passing interface commands. Separate memory allocation is assigned to the GPU to store the processed data after the CUDA threads have completed each kernel. The processed image data and classification results are copied to the CPU. Finally, features of the characterized defects are shown for the user.

### 3. Surface defect classification

Images grabbed by the CCD were processed to flatten the intensity distribution of the raw image. The normalized histogram was calculated for all pixels and stored in the allocated memory after equalization. A median filter was then used to reduce the noise by running a window of defined size across each pixel values of the equalized image. The output was stored in the allocated memory for noise reduction. The classification process of the recorded defect images is outlined in Figure 2, which follows BPN learning algorithm. Briefly, image moments of the training samples were calculated using the Hu set of moment invariants. For a 2D image with intensity distribution of $I(x, y)$, the raw moment of order $(p + q)$ of the image can be defined as

$$M_{pq} = \sum_{x} \sum_{y} x^{p}y^{q}I(x, y) \quad p, q = 0, 1, 2, \ldots$$
An image is summarized with functions of a few lower order moments and the central moments are

\[ \mu_{pq} = \sum_x \sum_y (x - \bar{x})^p (y - \bar{y})^q I(x, y) \]  

where the pixel coordinate \((\bar{x} = M_{10}/M_{00}, \ \bar{y} = M_{01}/M_{00})\) is the centroid of the image. The scale invariant can be achieved with normalizing the central moments as \(\eta_{pq} = \mu_{pq}/\mu_{00}^{\gamma}\), where \(\gamma = (p + q + 2)/2\). Hu introduced seven moment invariants that are changeless under image scaling, translation, and rotation.\(^{[11]}\) In these seven moment invariants, \(\theta_1\) and \(\theta_2\) are composed of second-order moments to feature the profile of a target, \(\theta_3\) to \(\theta_7\) are composed of third-order moments and used to describe the symmetry of the subject. Although the higher order moments can describe more details of the images, however, they are more susceptible to noise in the image. Therefore, this study only uses the first four Hu moment invariants of \(\theta_1\) to \(\theta_4\) to characterize the defects. The BPN network was then initialized by setting up all its weights \((W, \theta)\) as random numbers. The constants \(\eta\) (learning rate) and \(\alpha\) (momentum) were also assigned to approximate that of a sigmoid activation function.

Figure 2. Learning algorithm flowchart for defect inspection and classification.
After choosing the weights $W_1, \ldots, W_j$ and a bias $-\theta$ of the network layers, the sigmoidal function computes for each input $X_1, \ldots, X_n$ and the output pattern $Y_j$ according to the sigmoid

$$Y_j = \frac{1}{1 + e^{-\alpha \sum W_i X_i - \theta}}$$

Since all the weights are random, the calculation returns an output that is completely different from the target $T_i$. To quantify the deviation from the target, the algorithm computes for the error $\delta$, which is the difference between the target and actual outputs.

Next, backpropagation or backward passes to the output and hidden layers calculate the change in weights $\Delta W_i = \eta \delta W_i$ and $\Delta \theta = -\eta \delta$ until such that the output $Y_j$ is very close to the target. The mean square error (MSE) between the new weights for each successive iteration cycle is calculated. Once the MSE becomes sufficiently small and the set cycle time is completed, the weights are updated and given by:

$$W_{ij} \text{ (updated)} = W_{ij} + \Delta W_{ij}$$
$$\theta_j \text{ (updated)} = \theta_j + \Delta \theta_j$$

The updated weights will be used as the final weights for the classification of reconstructed defect maps. Here, the trained neural network only needs to extract the Hu invariants of the test sample without complicate image processing steps, which reduces the computational complexity of the classification. The training patterns used are currently limited to defect features that are found in touch panel glass according to the manufacturer. The defects consist of surface scratches that are elongated and narrow, and bubble-like features which can be attributed to dusts and other surface artifacts.

### 4. Results and discussion

The defect inspection and classification for a touch panel glass were implemented in this study. The dimension of the inspection surface is 43 mm $\times$ 229 mm. A single test runs using the linear CCD at a pixel resolution of 3.5 µm and 10 kHz linear rate generated $\sim$ 800 megapixel image. Surface features that exceed the size threshold set by the glass manufacturer are considered as defects, i.e., 3 pixels or approximately 10 µm. Representative defect maps of a pristine sample without defects and that with defects are shown in Figure 3(a) and (b), respectively. In Figure 3(b), the left side of the screen shows the overall detection range of the surface under test, which consists of 18 $\times$ 18 blocks. The red area on this map shows the region where defects exist. On the right side of the screen, there is a scrollable image that appears when you click each block of the map. Depending on the size of the object, each block typically consists of millions of pixels, and the image displayed was 700 $\times$ 3500 pixels. The most striking features differentiating the defects are the general shape and size of the defects. Surface features that are spot-like and with nearly circular edges measuring about 10 pixels or roughly 35 µm in diameter can be due to dusts deposited on the surface of touch panel or potential bubble inclusion in the material. The thin and elongated surface structures with thicknesses that range from 10 µm or more such as shown can be due to microfractures or light scratches on the surface.

To validate the effectiveness of the proposed classification method, three characteristic features observed in the touch panel glass were used for training the BPN algorithm. The number of training samples and representative images from actual inspection results for various types of defect combinations are shown in Table 1 and Figure 4, respectively. A fixed window size (350 $\times$ 350 pixels, 1 pixel = 3.5 µm) was used for BPN training to obtain scale-free learning tolerance for each type and size of defects. Moreover, the number of network nodes in the hidden layer of the BPN was set to 4, even though it can be arbitrarily chosen, so that the training cycle can also be reduced. As shown in Figure 5, the accuracy rate based on MSE of the updated weights was rapidly improved even with just a few iterations. For approximately 1000 cycles, the computed MSE was 0.0019, which means that the BPN algorithm can be executed fast enough without compromising the accuracy for classification.
Based on these results, the number of training iterations used in the algorithm was set to 1000. Other training parameters including the learning rate, momentum, and bias are shown in Table 2. The total time for training 100 samples was below 200 ms.

The classification results using actual defect images from the touch panel inspection equipment as test samples are shown in Figure 6. The map dimension in pixel numbers and relative defect size are

![Defect map construction](image)

**Figure 3.** Defect map construction of a (a) pristine sample without defects and (b) touch panel glass sample with surface defects.

| Type of defect | Number of samples |
|----------------|-------------------|
| Bubble         | 20                |
| Scratch        | 20                |
| Dust           | 20                |
| Bubble and scratch | 10            |
| Scratch and dust | 10              |
| Bubble and dust | 10                |
| Scratch and dust and bubble | 10 |
| Total          | 100               |

**Table 1.** Number of training samples used in BPN algorithm for defect classification.
Figure 4. Representative training samples for defect classification by BPN (image size: 350 × 350 pixels, 1 pixel = 3.5 µm). Note: BPN, back propagation neural.

Figure 5. Accuracy in BPN classification for different training cycles. Note: BPN, back propagation neural.
Table 2. Parameter values for 100 training samples in BPN.

| Training parameters | Values  |
|---------------------|---------|
| Cycle time          | 1000    |
| Learning rate (η)   | 0.5     |
| Momentum (α)        | 0.2     |
| Bias (θ)            | −1 to 1 |
| Training time       | 0.187 s |

| Image Size          | Test Sample | Classification Result |
|---------------------|-------------|-----------------------|
| 465 x 404           |             | Scratch               |
| 478 x 404           |             | Bubble                |
| 3169 x 1558         |             | Scratch & Bubble      |
| 657 x 602           |             | Scratch & Bubble & Dust|
| 350 x 350           |             | Bubble                |
| 350 x 350           |             | Scratch & Bubble      |
| 350 x 350           |             | Scratch & Bubble      |
| 350 x 350           |             | Bubble & Dust         |
| 350 x 350           |             | Scratch & Bubble & Dust|

Figure 6. Classification results of actual defect samples.
shown. Experimental results show that the accuracy of the BPN algorithm was established based on 100% classification outcomes irrespective of defect orientation. Although the contrast of the defect images in Figures 4 and 6 is poor, the relatively low visibility levels of the test samples have no apparent impact on the classification results, which implies that the most dominant characteristics of the defect as defined by its geometry and relative size are more crucial for classification training. The use of varied training samples with size, shape, and orientation such as shown in Figure 4, for instance, has been verified to improve the classification outcome of the actual test samples using less iterations.

It is worth mentioning that sometimes the geometry characteristics for bubble and dust are similar. To resolve the ambiguity of classifying mixed defects, the BPN training for multiple defects is the focus of our efforts. However, it can be distinguished from the intensity level of the original images. The image intensity of light scattered from a dust is usually more intense than the scattered illumination from bubbles and scratches. Therefore, the issue of image intensity is also accounted during training. Despite this limitation, it should be emphasized that the classification process for a 350 × 350 pixel image can be completed in 0.1 ms. Combined with the fast parallel computing in GPU for the reconstruction of defect images, a fully integrated high-resolution inspection platform for detection and subsequent defect classification is very feasible using the proposed setup. The training of higher number of samples as well as identification of actual defects can help improve the defect classification catalogue for touch panel technology.

5. Conclusion

An AOI system with high-resolution detection capability and accurate defect classification scheme was developed. The processing of large image data acquired by the imaging module was implemented by a GPU. The reconstructed images were shown as defect maps, where a neural learning algorithm is used for defect classification. The BPN approach was shown to be computationally simple, fast, and accurate. The classification scheme based on image moment invariants demonstrated excellent ability of classifying common defects in touch panel glass even if the number of iterations and training samples used were small. It is possible to perform the classification of multiple defects for various products by further training the algorithm to catalogue different defect types. Thus, the improved system can be used to streamline the inspection and sorting process for overall improvement in production lines.

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