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Intelligent assessment of subsurface cracks in optical glass generated in mechanical grinding process

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ABSTRACT

Grinding process of optical glass has been reported to be related with the creation of subsurface cracks. However, for the time being, most measurement methods have been depended on human operations. In this paper, an intelligent assessment method based on image processing technique is proposed. Grinding trials proved that, the proposed method can accurately (with the biggest relative error of 3.53%) and quickly (nearly 1.6 seconds per micrographs) recognize and measure the subsurface crack depths. More importantly, the proposed method has good robustness to different-sized images. Besides, the method does not require any input parameters or any adjustment of thresholds, therefore the method does not require any prior knowledge of either mechanical grinding process or brittle material behaviors relating with subsurface cracks. Based on above, the proposed method is expected to be meaningful to both metrology equipment companies and optical glass manufacturers.

1. Introduction

As a key kind of optical materials, manufacturing of optical glass is considered as the foundation of many industries including optics, telecommunication, electronics, and mechanotronics [1]. The mechanical grinding process of optical glass, however, has been reported closely related with the generation of subsurface cracks [2–4] due to the unstable grain-workpiece interactions induced by stochastic grinding wheel topography [5–7], although more advanced grinding tools with uniformly-protruded monolayer abrasives were produced [8–10].

With this, substantial studies relating with the quantification of subsurface crack depths have been reported so far. Although many measurement methods have been provided, nearly all of them have been suggested based on the cross-section micrographs observed by an optical microscope, where many human involvement/operations have been required, because, as seen in Fig. 1,

- In most measurement cases, the ground surfaces of optical glass have been obliquely placed, therefore the subsurface damage (SSD) depth should be the tilted distance labeled by “SSD” in Fig. 1;
- Due to the polishing operation during the creation of sample cross sections, many noise points have been introduced (see “noise” in Fig. 1);
- Material flaws might also interfere with the SSD measurement.

However, it should also bear in mind that, human measurement of SSDs might be only feasible when a small quantity of operations are required. Therefore a more advanced automated measurement of SSDs is highly in-demand.

On the other hand, intelligent recognition and measurement based on image processing technique has been recently found as a powerful tool in many fields containing mechanical, civil and agriculture engineering. This technique can be used for not only detection of a certain macro/micro feature, but also quantification of a certain process to provide a more in-depth understanding.

In mechanical and manufacturing engineering, both Zatočilová et al. [11] and Du et al. [12] proposed an image-based method to on-line measure both the dimension and the axis straightness of the hot forgings. Experiments for both unheated and heated samples showed the method accuracy of up to 97%. Zhao et al. [13] used an image-processing-based method to detect the defects in the cold rolling process with the consideration of the influence of industrial liquids and surface textures. The defect detection accuracy achieved 91% although some defects were covered by industrial liquids. A similar method was also reported in the monitoring of the brittle material grinding process [14], enabling the automation of observations of process details. The method was also employed to in-process and in-situ monitor ground surface morphologies [15], where the brittle and ductile regions can be achieved during the machining process, providing the reference of the process statuses. Besides, Gadelmawla [16] employed the image-processing method to measure the screw thread features.

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Nomenclature

i, j	example pixel
$V_{i,j}$	3*3 pixel matrix around pixel i and j
Ω_i	L*L pixel region around pixel i
I_i	grey value of pixel i
O_i	grey value of pixel i after denoising
w_{ij}	similarity between pixel i and j (see Eq. (2))
z_i	normalized coefficient (see Eq. (3))
h	smoothing factor
μ	randomly selecting three clustering centers
$P(\mu\|j)$	degree of membership between the center μ and the pixel j
d_{rj}	grey value difference between the center μ and the pixel j
N	total pixel number in the image
J_{fuz}	objective function during clustering
B	cross-shaped structure matrix
$\mathbf{I}$	matrix containing the color information of the input image
a	a certain element in the matrix $\mathbf{I}$
$\mathbf{B}$	shrinkage matrix
$(x_{\max}, y_{\max})$	coordinate of the deepest pixel of the detected subsurface cracks
S_{length}	scale bar length (with the unit of μm)
S_{pixel}	scale bar length (with the unit of pixels)

The method followed the standard ISO metric thread plug gage and the maximum difference between the standard and measured values was found to be smaller than ±5.4 μm.

In civil engineering, Valença et al. [17] and Dogan et al. [18] assessed cracks on the concrete bridge by using images captured by terrestrial laser scanning technology. The method can achieve highly-localized results where the crack width, length and orientation can be accurately recognized and measured.

An interesting application of the image-based measurement in agriculture engineering was reported in Ref. [19]. The authors used image processing technology to monitor the automatic drying system of rough rice. The system sent the acquired images of rough rice to a computer for image processing so that the distribution of stalks and the moisture content of rough rice could be obtained.

Besides, various image-based measurement methods were used to measure plasma temperature [20], thin oil film thickness [21], particle velocity [22], 3D deformation [23,24], bubble [25] and multiphase flow [26] behaviors, showing good robustness, high detection and measurement speed, and high accuracy.

Based on above, an image-based intelligent assessment method is proposed in this paper to measure SSDs in optical glass generated in mechanical grinding process. The method aims to enable the automated recognition and quantification of SSDs, so that the quick, accurate, and large quantities of measurements can be performed by computers. The method therefore is expected to be promising to facilitate the industrial manufacturing of optical glass.

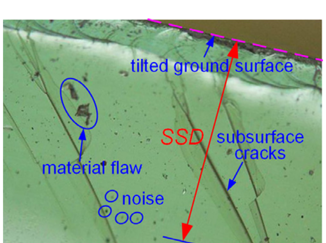

Fig. 1. Cross section image showing the problems during the measurement of subsurface cracks.

2. Method details

The proposed methodology mainly includes three steps (see Fig. 2): (1) detection of the subsurface cracks, (2) recognition and reconstruction of the ground surface, and (3) calculation of the SSD depths.

2.1. Detection of the subsurface cracks

The detection of the subsurface cracks is one of the most important steps in this study. It mainly includes four substeps: (1) non-local means denoising, (2) fuzzy c-means clustering, (3) morphological dilation of subsurface crack edges, and (4) morphological erosion and reconstruction of subsurface crack edges.

2.1.1. Non-local means denoising

As illustrated in Fig. 1, both noise pixels and material flaws would interfere with the detection and measurement of SSDs, therefore the first substep is to denoise the input image. Here the non-local means denoising [27] is used because, in comparison with other denoising methods, this method was proved to be very effective to denoise randomly-scattered noise pixels whilst retaining all the edge details in the micrographs [27] so that subsurface cracks would not be influenced.

As seen in Fig. 3(a), the basic principle of this method is as follows: for a certain pixel i in the image, each 3*3 pixel matrix (with the center pixel j, symbolised by "matrix V_j" in Fig. 3a) within the neighboring range L*L pixel region (denoted as the region Ω_i) is compared with the pixel i neighboring matrix (symbolized by "matrix V_i" in Fig. 3a).

Assuming the original grey value of pixel i is I_i, then the denoised grey value of pixel i (denoted as O_i) would be

$$O_i = \sum_{j\in\Omega_i} w_{ij} \cdot I_j \quad (1)$$

where w_{ij} refers to the similarity between pixel i and j, and could be calculated by

$$w_{ij} = \frac{1}{z_i} \exp\left(-\frac{\left\|V_i - V_j\right\|^2}{h^2}\right) \quad (2)$$

where z_i and h are separately the normalized coefficient (calculated based on Eq. (3)) and the smoothing factor (set to be 2 according to Ref. [27]), and the operator $\| \bullet \|$ denotes the norm.

$$z_i = \sum_j \exp\left(-\frac{\left\|V_i - V_j\right\|^2}{h^2}\right) \quad (3)$$

Fig. 3(b) and (c) separately show the original and the denoised micrographs containing subsurface cracks.

2.1.2. Fuzzy c-means clustering

For most micrographs, they generally have three different kinds of regions: (1) background (called dark region), (2) crack region (the target region in this study), and (3) bulk material region. Here the fuzzy c-means clustering [28] is employed in this study to divide the whole image into three regions.

The basic procedures of the method are: (1) randomly selecting three clustering centers (denoted as μ) for the three regions, and then calculating the Degree of Membership (DM) of each pixel (assuming the pixel j) in reference to the centers $P(\mu|j)$ according to