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Multiple Cameras Characterization for Float-Zone Crystal Growth Production

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Abstract
The number of applications where silicon wafers are used has grown exponentially: integrated circuits, solar cells, and power electronics. In the industrial setting, the production of ultra-pure monocrystalline silicon ingots, required for high-power applications, has to be carried out using the Float-Zone (FZ) method. To obtain a high-quality final product, it is essential to continuously monitor the growth chamber with different sensors as well as with a camera vision system. Information extracted from the acquired images is then used to regulate process parameters and maintain working conditions as close to its nominal values as possible [3]. The decision-making process responsible for the regulation of the parameters operates under the assumption that all machines function under the same conditions. The procedure for adjusting camera focal length is carried out manually and relies on an algorithm that scores image quality in real-time based on blur content, by processing frames as the focal length is adjusted to maximize the quality score. The results showed that the current algorithm is affected by lighting conditions as well as region of interest (ROI) size, and signal noise, highlighting the need for a more robust algorithm to ensure a consistently high-quality image acquisition. This study identifies an algorithm that shows variation related to signal noise sensitivity of only 0.33% compared to the fluctuation of 1.40% in the currently implemented method and proposes a new method that is more robust to changes in contrast within the image.

Float-Zone crystal growth; image quality assessment; blur content; focal length adjustment

1. Introduction

As the demand for silicon wafers rises, it is necessary to increase productivity while maintaining low production cost. Two methods are mainly used industrially: the Czochralski (CZ) method and the FZ method. CZ requires a silica crucible, leading to high oxygen incorporation in the crystal. In the FZ the crucible is removed but more expensive feeding rods are needed to maintain a stable molten material pool, making increasing crystal yield, by maximising the number of wafers produced form each batch, crucial. Since it is a time-consuming batch process, having defective pieces leads to a waste of both material and energy invested. To guarantee a high-quality product, proper parameter regulation is necessary. The decision-making process is also based on data acquired through cameras, as the images are processed to extract important information and detect defects. Since the central control system of the machine, which receives all the data from the current run and regulates the parameters using also data from an archive of previous runs, works under the assumption that all machines operate under the same working conditions, being able to guarantee consistent image quality ensures that the information extracted through image processing is valid. To achieve satisfactory image quality across all the cameras used, it is necessary to use an algorithm to score image quality based on focal blur content. The human brain is able to assess whether an image is sharp or not, but it is a subjective and qualitative statement and, as such, inconsistent. Instead, using an algorithm allows for an objective quantification of image quality based on blur content. Since focal blur has not been yet fully characterized as a phenomenon, many different algorithms have been developed over the last decades each considering a different feature of the image as the most representative of blur content.

2. Image Quality Assessment

Digital images are nothing more than 2D discrete signals and can therefore be represented and processed in different domains. Images are typically acquired by cameras in the spatial domain, but they can be converted to the spectral domain using the Fourier transform. Working in the spectral domain is much less intuitive, but it allows for faster computation of convolutions, an operation widely used in image processing to enhance features of an image by filtering it through masks of different sizes and shapes. In literature, many examples of methods developed in both the spectral and spatial domain can be found. In this paper a method based on the magnitude component [1] of the Fourier-transformed image (MAG) and a spatial method based on the quadratic index of fuzziness [2] of the intensity gradient (QIF) are compared. Many tests were conducted to determine which method is better suited for this specific application.

3. Experiments

To assess the performance of both algorithms many tests were conducted to identify which features of an image might affect the quality score. Although both algorithms are No-Reference methods (meaning they can assess image quality using only the distorted image acquired through the camera), it was decided to also test them on a set of pristine digitally generated images. The images in the set differed in the shape, size and location of the subject but, being generated using a script, were all pristine (free of artifacts and blur) and therefore as sharp as possible. Ideally, an algorithm developed to assess image sharpness would score all pristine images equally, regardless of any features not related to blur content. It was shown that both methods were affected by subject size and shape, while the score remained consistent when its location within the image was changed. It was also highlighted that contrast affected the quality score by testing different intensities for the foreground and the background. Further testing with images acquired with a camera at different focal lengths proved that both methods are able to score blur content and can be used to assist the focal length regulation process. However, using an algorithm that is not affected by contrast or ROI size would increase score comparability across different machines, since lighting conditions vary significantly. The ROI itself is affected by lighting conditions since different portions of the checkerboard can be obscured by machine components. The purpose of this study is to find an algorithm that ensures consistently high-quality image acquisition. The final part of testing involved real-time scoring of images acquired as a live video stream from the camera. In such applications, computational time becomes crucial. Both methods are able to keep up with the camera's frame rate, scoring frames at a rate of about 30 frames per second. Therefore, the delay between the frame shown and the quality score displayed is negligible. It was highlighted, during the focal length regulation process, that both methods showed fluctuations even when the focal length of the camera wasn't being changed, indicating that both were affected by signal noise. The MAG and QIF algorithms showed variations of about 1.4% and 0.33% respectively. Using an algorithm that is less sensitive to a random phenomenon like signal noise helps achieve image quality consistency across multiple cameras.

3.1. Exponential variant of Quadratic Index of Fuzziness

The quadratic index of fuzziness score is defined within a closed interval between 0 and 1, where higher values indicate better the image sharpness. When testing the method there were small variation in the score value assessing images with different levels of blur simulated through Gaussian filtering. Since the method proved to be correlating well with blur content, both simulated and focal blur, it was decided to introduce a non-linear rescaling of the score to amplify score variations.

$$QIF_{exp} = e^{1 - \frac{1}{QIF}}$$

Using this equation maintain the original score range while increasing the differentiation, in terms of score value, between sharp and out-of-focus images. However, rescaling the original QIF score also increases the sensitivity to noise resulting in score fluctuations of approximately 3.2%.

3.2. Contrast enhancement algorithm and QIF

Since the output score of the QIF algorithm is computed based on an evaluation of the intensity gradient using Sobel masks, this method is particularly sensitive to contrast and, consequently, to lighting conditions. While contrast and blurriness are often related, low contrast does not necessarily imply a lack of sharpness. To solve this issue it is possible to apply intensity normalization during image filtering. The underlying principle is that if, within the 3x3 neighbourhood considered at each step of the convolution, the maximum intensity difference exceeds a predefined threshold, then the gradient is most likely associated with an edge and is therefore useful to evaluate image sharpness. By linearly rescaling the intensity values so that the highest intensity is mapped to 255 and the lowest to 0, lighting conditions do not affect the score. Whereas, if the maximum difference is below the threshold, then the gradient is to be associated with actual blur and rescaling the contrast would introduce artifacts distorting the results. The effectiveness of this new algorithm was tested on a set of images extracted from the industrial videos available. From the sharpest frame of each video two portions of the checkerboard were selected. Each pair of images created from the videos (see Figure.1) only differs in lighting conditions and should therefore have the same quality score as they share the same blur content. The exponential variant implemented with the contrast enhancement algorithm best approximates the ideal behaviour (see Figure.2).

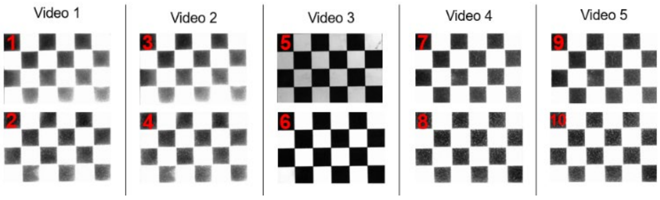

Figure 1. Set of images of left and right portions of the checkerboard

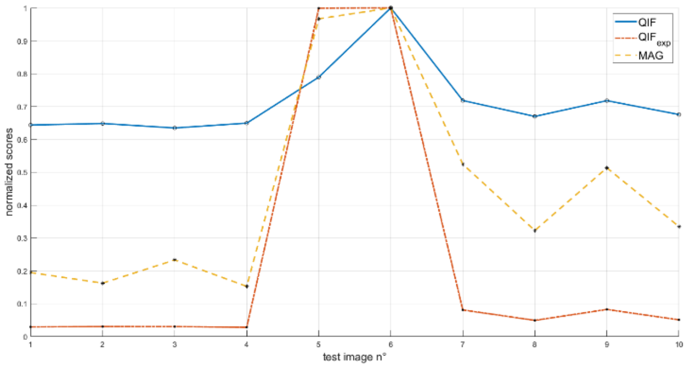

Figure 2. Trends on the set of images created from industrial videos

4. Conclusions

The results obtained throughout the testing process show that the QIF method is better suited for this application compared to the MAG algorithm. While both methods show similar sensitivity to blur, the QIF algorithm is less affected by noise, exhibiting a 76.4% reduction in fluctuation amplitude, facilitating the focal length adjustment procedure. Combining the QIF and contrast enhancement algorithms ensures better score comparability across different machines operating under varying lighting conditions. As shown in Figure.2 the new method still exhibits variation in the score between the left and right sides of the checkerboard, but those associated with lighting conditions, normalised relative to the variations related to blur content, show that fluctuations were reduced by 89.5% compared to those of the MAG. The contrast-enhanced algorithm exhibits the best performance, but its significantly increased computational load reduces the number of frames scored per second by a factor of 30, compromising the possibility of real-time implementation. The exponential variant showed increased sensitivity to noise, displaying variations of around 3.2%. Characterizing the signal noise could help reduce noise sensitivity, while optimizing the script would reduce computational time. Future activities will address both issues, enabling the real-time implementation of the exponential variant of the contrast-enhanced version of QIF, ensuring robustness against both noise and lighting conditions.

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