Nigerian Journal of Technology (NIJOTECH)
Vol. 41, No. 3, May, 2022, pp.585-590
www.nijotech.com

Print ISSN: 0331-8443
Electronic ISSN: 2467-8821
http://dx.doi.org/10.4314/njt.v41i3.19

The Effects of Camera Focus and Sensor Exposure on Accuracy Using Computer Vision

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Abstract

As industrial camera become smarter, due to the increase in supporting algorithms, so the quality of data produced offers higher precision and accuracy of industrial inspection operations. This paper aims to focus on the accurate effect of camera focus on a calibration process under the influence of different sensor exposure and degrees of focus. A computer vision methodology is used to determine the effects of different sensor exposures and at different degrees of camera focus. Endocentric and telecentric lenses are used to acquire images, and a comparative analysis was achieved using the least square method. A sample of 2176 images was used to generate the population for analysis. The analysis showed that the human eye cannot visually determine a hundred percent focus of an image. This means that it is difficult to determine when an image is 100% focused from when it is 95% focused. The result from the experiment showed that as the camera focus tends towards 100% the calibration error decreases, with a minimum calibration error of 0.06 pixels, leading to the conclusion that the developed method achieved a calibration error accuracy with the most effective camera sensor exposure and the camera focus.

Keywords: Calibration Error; Accuracy; Camera; Sensor Exposure; Uncertainty

1.0 INTRODUCTION

The accuracy effect of a well calibrated system cannot be over-emphasized, due to the benefits it gives to the system. In machine vision, calibration is used to convert dimensions in the image coordinate plane to world coordinate [1]. This conversion primarily gives direct effects to the metrological system. For accurate and precise measurement to be taken, the calibrated system has to possess very little or no error rate [2]. However, as this is almost impossible to achieve, giving several factors, the evaluation of the degree of uncertainty is used to compensate for the error rate. Computer vision algorithms are developed to perform inspections to determine the precision and accuracy measurement systems [3].

Camera calibration can be greatly influenced by various factors ranging from perspective to ambient light effects [4-6]. In this paper, a focus algorithm is used to determine the effects of sensor exposure and focus range in a calibration process. This paper aims to expose the degree of image focus, under the influence of sensor exposure to light, that is, adequate for a successful calibration. The experiment performs structured-type calibration on images taken with endocentric and telecentric lenses. A sample of 2176 images was used to generate the population for analysis. The analysis of the camera focus on the calibration process shows that the human eye cannot visually determine a hundred percent camera focus of an image. This means that it is difficult to determine when an image is 100% focused from when it is 95% focused. However, the existence of this difference, even if negligible, plays a vital role to determine the effect of the calibration error and the measurement error generated.

In this paper, we determine the difference in the camera image between the focus of 95%, 97% and 100%. The experiment shows that the calibration error reduces as the focus tends toward 100% and the subsequent measurements as well. The difference, even though small, has an evident impact in determining the accuracy of the calibration process. Calibration is used to convert dimensions in the image coordinate plane to the world coordinate plane [7]. This conversion primarily affects the metrological system. Chen *et al* [8] developed a computer vision based approach that utilized a recurrent neural network-based deep learning algorithm to recognize pig

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enrichment engagement behaviors. The study proposed an algorithm could recognize objects with accuracy of 96.5%, 96.8% and 97.6% respectively. Livingstone *et al* [9] used an automated machine learning approach to build a computer vision algorithm for orthoscopic diagnosis capable of greater accuracy than trained physicians. This algorithm could be used by primary care providers to facilitate timely referral, triage, and effective treatment. Computer Vision system measures with high accuracy of the position and orientation of objects in order to improve the actual object positioning system [10]. Ramirez-Hernandez *et al* [11] proposed a camera calibration method that uses the least square method to model the error caused by the image digitization and the lens distortion. The proposed method was applied in the stereo vision systems, and a comparative analysis between the real and calibrated three dimensional data points is performed to validate the improvements. Lui *et al* [12] developed a method to automatically identify and locate tail biting interactions in group-housed pigs taking a computer-based approach. The method employs a tracking-by-detection algorithm to simplify the group-level behavior to pairwise interactions. The performance of the proposed method was evaluated by quantifying the localization accuracy and behavior classification accuracy. Li *et al* [13] proposed a study aimed at evaluating the diagnostic performance of deep learning models in the detection and classifying of pneumonia using chest X-ray images. The method indicated high accuracy performance in classifying pneumonia from normal chest X-ray radiography and also in distinguishing bacterial from viral pneumonia. However, major methodological concerns were not addressed in the study. All of the aforementioned studies only consider computer vision techniques from the perspective of accuracy with no intent on the effect of the camera sensor exposure. This paper intends to address the issue from both perspectives.

Automatic camera focus revolutionized the digital image world [14]. With automatic focus, quality images can be acquired from a wider range of camera quality specification. This has proven to be reliable in a non-industrial setting. However, in industrial inspections, automatic focused cameras are not used because of the random nature and change of the working distance. In order to be well safeguarded on this danger, the use of a manual camera focus is often times proposed. With a manual camera focus, more control can be achieved regardless of the change or random nature of the working distance. Nevertheless, this option poses a great challenge on the achievement of a well-focused image capture [15]. The specification and quality of a camera used for a computer vision application is paramount to the successful completion of an experiment. Most often, there is a need to put into consideration the camera specifications before carrying out the experimentation [16]. This is due to the fact that the quality of the images processed during the processing of analysis determines greatly the effects of precision and accuracy of the results. In an industrial calibration process [17] [18], where the working distance is constant, the use of a manual focus camera is necessary due to factors such as, the distance between the object and the camera, which usually affects the focus and focal length of the lens, the size of the object, which determines the field of view (FOV), the camera exposure, which determines how the lighting can be controlled or whether the object is lucent or not [19]. These parameters make selecting the proper lens for an accurate calibration a challenge. A focused lens manifests evidently the manner in which the image from the world is reproduced on the sensor, which could be adjusted manually or automatically.

The analysis of a computer vision system often leads to a decision on the type of lens to be used for acquisition of the image [20]. There are three categories of lens options: endocentric, telecentric and hypercentric [21]. The endocentric lens capture images of an equal perspective as the human eye [22] [23]. It is commonly referred to as the standard fixed focal-length lens. The telecentric lens erases perspective errors [24-26]. The hypercentric lens inverts the normal perspective to see almost the entire surface of a three-dimensional object. This paper does not consider the hypercentric lens.

The paper is arranged as follows. Section 2 describes the material and method. Section 3 describe the result and verification, and Section 4 describes the conclusions from the research.

2.0 MATERIAL AND METHOD

To accomplish the desired outcome, the set-up used for the experiment includes a Manta G-504 camera with an endocentric lens of 16 mm and a telecentric lens TC12056. All images have been taken from a 145.1 mm of working distance for the endocentric lens and 157.8 mm of working distance for telecentric lens. The back-light used was the BIBL-W130-110 for endocentric experiments and the LTCLHP056-G for telecentric, both using a transparent calibration pattern of 80x60 mm. Halcon HDevelop 13 development framework was used for analyzing the acquired images. Halcon provides several algorithms for segmentation, filtering and determining the sharpness of an image, such as thresholding, Sobel amplitude and intensity function. Thresholding was used to select and segment the pixels from the acquired images. Then the Sobel amplitude tool was used to calculates the derivative of an image as an edge detector. The intensity function was used to calculate the mean and deviation of the gray values in the input image.

With the acquired Sobel amplitude and intensity function we obtained the mean and standard deviation range of values of the focused images. An angular tilt of 20° and 30° of the calibration plate where used to further verify the claim for consistency.

3.0 RESULT AND VERIFICATION

To perform the calibration experiment, 2176 image samples where acquired: 1632 from the endocentric lens and 544 from the telecentric lens. The images acquired with the endocentric lens in this experiment are grouped into three categories:

Center plate no tilt: 8 images of the calibration plate were acquired with no angular tilt. The camera exposures range between 5000:1000:8000, with autofocus alignment at 95, 97 and 99 degrees. The acquired image files total 96.

Corner plate 20° tilt: The angular tilt of the calibration plate is 20◦. For each position of the tilted corner, images of the calibration plate with the corresponding plate rotation is acquired. The camera exposures range between 5000:1000:8000, with autofocus alignment at 95, 97 and 99 degrees. The acquired image files total 768.

Corner plate 30° tilt: The angular tilt of the calibration plate is 30◦. For each position of the tilted corner, images of the calibration plate with the corresponding plate rotation is acquired. The camera exposures range between 5000:1000:8000, with autofocus alignment at 95, 97 and 99 degrees. The acquired image files total 768.

The images acquired with the telecentric lens are grouped into three categories:

Center plate no tilt: 8 images of the calibration plate were acquired with 8 corresponding plate rotation. The camera exposures range between 6000:1000:9000. No autofocus alignment required. The acquired image files total 32.

Corner plate 20° tilt: The angular tilt of the calibration plate is 20◦. For each position of the tilted corner, images of the calibration plate with the corresponding plate rotation is acquired. The camera exposures range between 6000:1000:9000. No autofocus alignment required. The acquired image files total 256.

Corner plate 30° tilt: The angular tilt of the calibration plate is 30◦. For each position of the tilted corner, images of the calibration plate with the corresponding plate rotation is acquired. The camera exposures range between 6000:1000:9000. No autofocus alignment required. The acquired image files total 256.

The result from the experiments shows that the degree of autofocus at 99 percent is consistent for all the distinct scenarios of positioning and tilting. The algorithm effectively makes the realization of the best calibration when the image is ultimately focused. Even though the calibration error difference between the 95 and 99 percent focus are not spatially distinct, the results indicates a consistent success rate of calibration at 99 percent. Figure 1 shows the graph analysis of the endocentric lens.

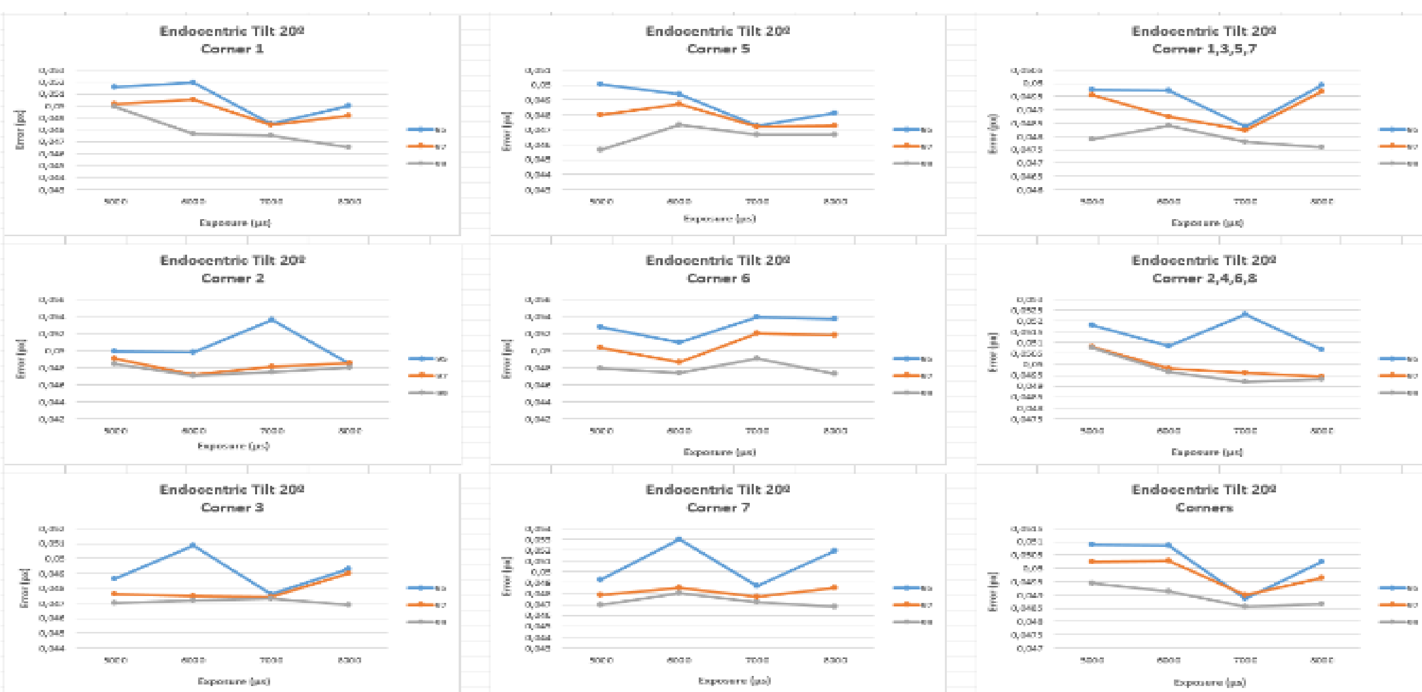


Figure 1: Analysis of the endocentric lens

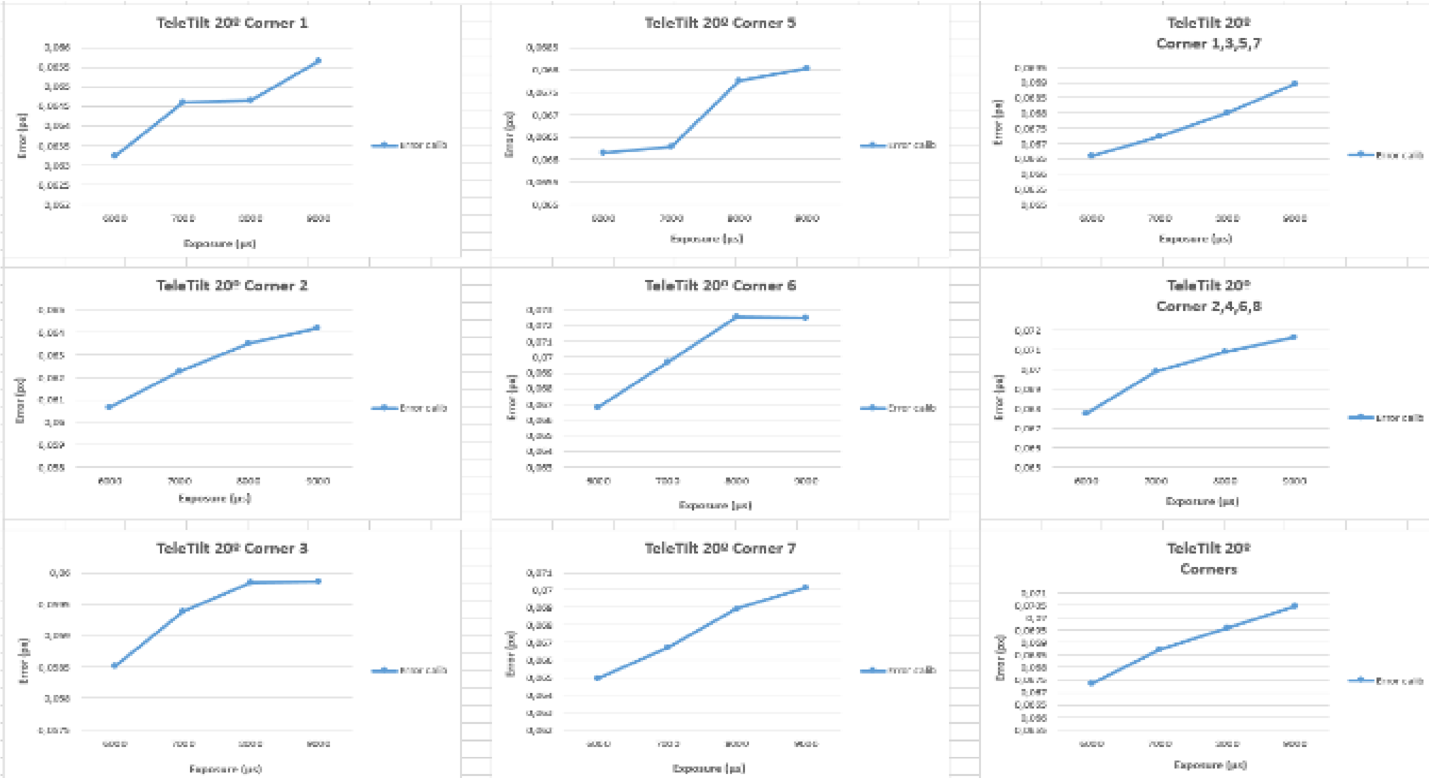
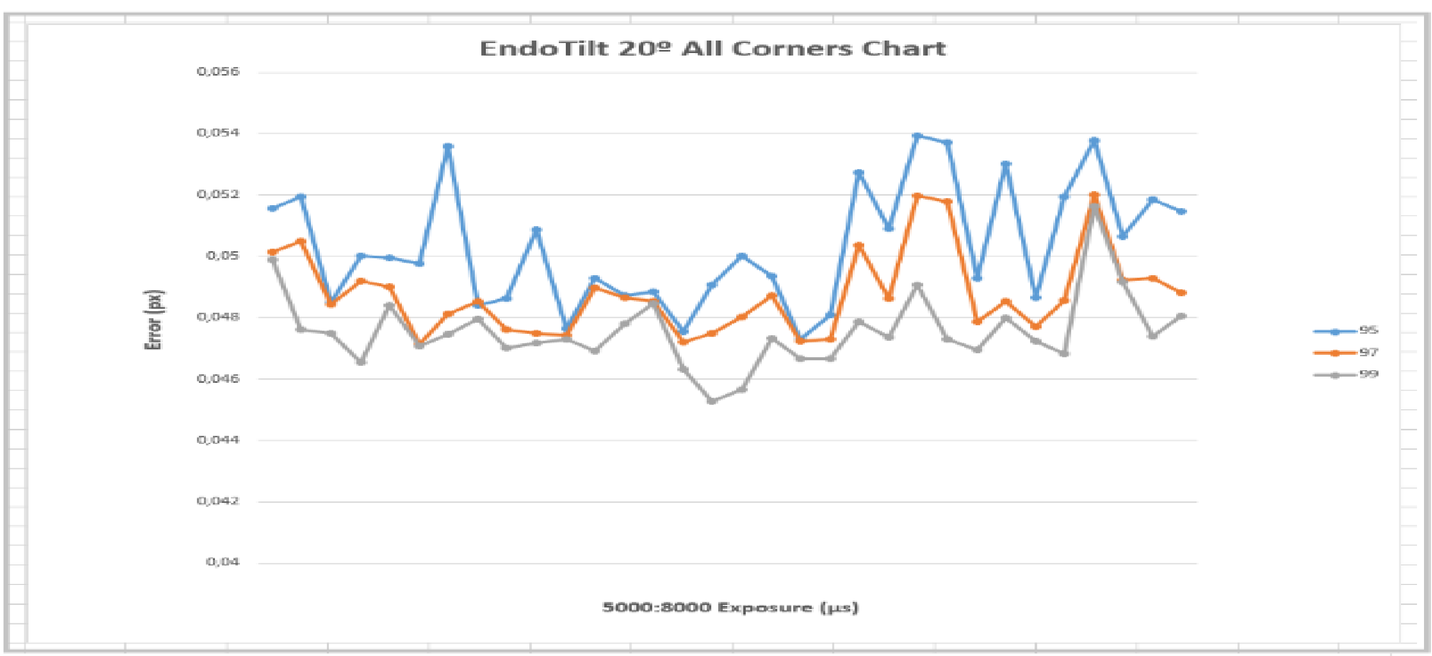


Figure 2: Analysis of the telecentric lens

Furthermore, the result from the analysis on the telecentric lens acquisition also show a consistency in the error rate. Moreover, the result shows more clearly the steady effect of camera exposure to the calibration error. Unlike the endocentric lens, the telecentric lens is more sensitive to sensor exposure. However, although the endocentric lens is less sensitive to camera exposure, the calibration error result is lower. Figure 2 shows the graph analysis of the telecentric lens.

Figure 3 shows the calibration error relationship between the focus range at 20 and 30 degrees of angular tilt.



(a)

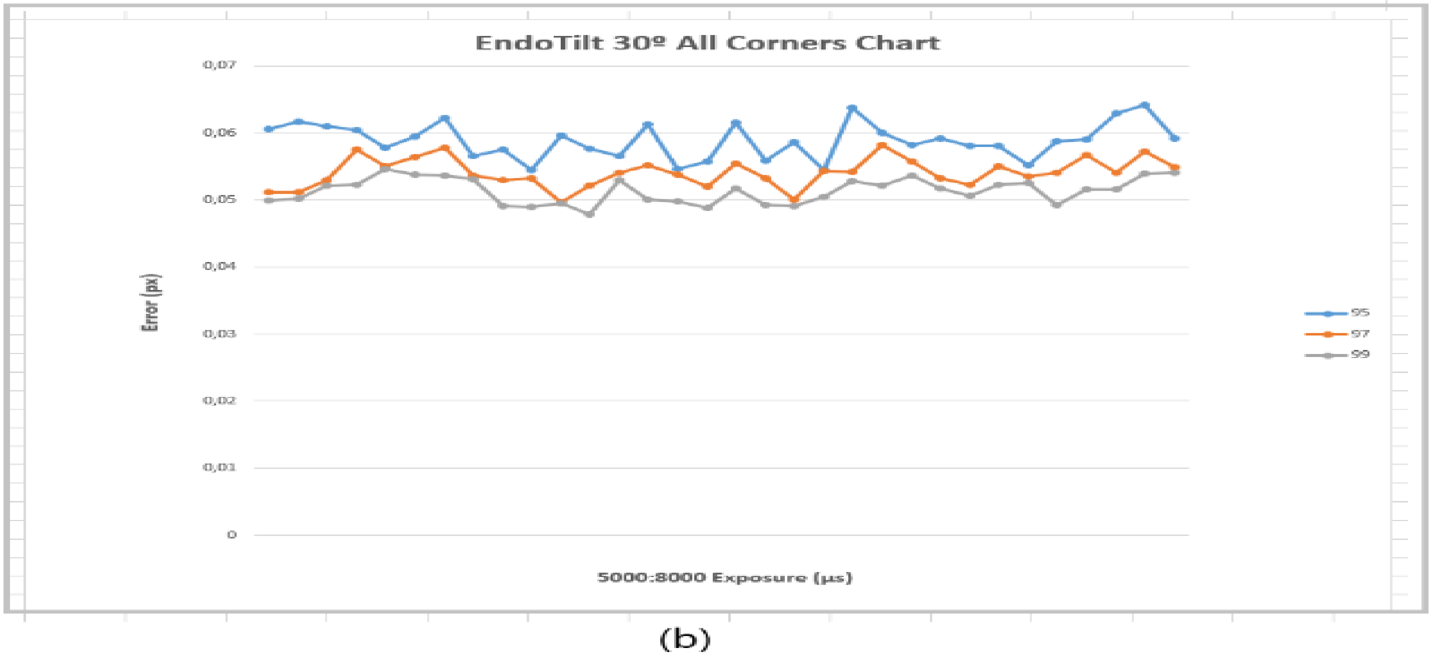


Figure 3: Analysis of calibration error (a) 20° angular tilt (b) 30° angular tilt

4.0 CONCLUSION

The analysis shows that the human eye cannot visually determine the 100% focus of an image. This means that it is difficult to determine when the image is at 100% focus and 95% focus. However, the existence of this difference, even if insignificant, plays a vital role in determining the influence of calibration errors and the resulting measurement errors. In this paper, we determined the image differences between 95%, 97%, and 100% camera focus.

The experiments have shown that as the focus tends to 100% and subsequent measurements, the calibration error will decrease. Although the difference is small, it has a significant impact on the accuracy of the calibration process. The results show that the developed method achieved high calibration error accuracy with the most effective camera sensor exposure and best focus, with an uncertainty of 100%.

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