International Journal of Mathematical, Engineering and Management Sciences
Vol. 8, No. 5, 841-849, 2023
https://doi.org/10.33889/IJMEMS.2023.8.5.048

Computational Metrology for Measuring Industrial Component Dimensions

Lokendra Singh
School of Mechanical and Materials Engineering,
Indian Institute of Technology Mandi, Kamand, 175005, Himachal Pradesh, India.
Corresponding author: singhlokendra.iit@gmail.com, d19041@students.iitmandi.ac.in

Arpan Gupta
Department of Mechanical Engineering,
Indian Institute of Technology Delhi, 110016, New Delhi, India.
E-mail: arpan.gupta@mech.iitd.ac.in

(Received on January 27, 2023; Accepted on June 22, 2023)

Abstract
To target the problem of dimension measurement of objects in industry, a new computer vision method is proposed based upon Harris-corner detection. The proposed research delivers an alternative to the requirement of various precise measurement devices and skilled labour. In order to measure the various dimensions of an object, the proposed algorithm separates the corner points from the background based on variations in pixel intensity. An algorithm has been proposed to analyze captured object images and perform measurements and inspection processes. The aim of this paper is to utilize computer vision detection algorithms to control the quality of manufactured parts by sorting them on size tolerance. The length of various objects such as screws, bolts, and a rectangular iron piece was determined from the images captured using smartphone camera (Samsung Galaxy F62). The evidence for a total of eight different measurements is presented, and the accuracy of the method is proved up to 99 percent against the dimensions measured using the Vernier calliper.

Keywords- Dimension measurement, Computer vision, Smartphone camera, Spatial parameters.

1. Introduction

Measuring the exact dimensions of parts is an important task in the manufacturing industry. The more accurate dimension of a part produced by a manufacturer indicates the quality of the lot in a production. The geometrical size and accuracy have a significant impact not only on mechanical efficiency and durability, but they are also important in reducing environmental pollution and energy usage. Current methods of dimension measurement are either time-consuming or costly. Besides that, there are very few existing measurement methods that can measure all the visual features and reduce the measurement time to some extent (Hashmi et al., 2022). Metrology can be viewed as a challenge to guarantee the quality of parts (Alonso et al., 2019). It requires good expertise to control 100% of the production while maintaining the necessary flexibility to adjust the system according to the various sizes of the production components (Wang and Alexander, 2016).

The growing concern about quality control as a result of new market restrictions in recent years has necessitated the development of process technology geared towards more reliable tests and new methods of monitoring product quality (Flugge et al., 2002; Gomes and Leta, 2012). A geometric dimension measurement system for shaft parts based on machine vision is presented, where it uses the CCD (Charged coupled device) camera to get the images (Li, 2018b). First, it pre-processes the collected images, and then a canny detection operator is applied to extract the edge contour of the part image. A sub-pixel edge detection with a Logistic edge model was proposed by Chen et al. (2014) for measuring the workpiece dimension to detect and eliminate unqualified ones, and the method consists of various integral and differential operations for estimation as compared to the simple linear conversion scale used for calibration.

A great number of methods have been developed for the acquisition of object measurements, including size, shape, colour, and texture, in the past few decades (Li, 2018a). Because of the limitless variation of texture patterns and the lack of a formal scientific definition for image texture, Zheng et al. claim that there is not yet a perfect procedure for each sort of measurement, especially texture measurements (Zheng et al., 2006).

The application of computer vision is not only limited to the manufacturing industry; the study proposed by Li et al. discusses non-invasive plant phenotypic measurement (a set of observable characteristics such as height, length, and colour or traits of an organism) and evaluation approaches to replace traditional artificial and destructive extraction methods (Li et al., 2020). It also attracts computer vision researchers to work on image-based plant phenotyping and theoretical analyses of plant phenotyping based on computer vision. White et al. (2006) presented a study to develop the next generation of fish sorting equipment, employing modern hardware and programming techniques to identify species and measure length with errors of less than 1 cm. The work proposed by Veeraraghavan et al. (2003) compares the actual measurements with the anticipated height and length data using computer vision technology. It also approximates the shapes of a turning vehicle and a vehicle with geometric distortion.

A non-contact measurement system proposed by Gadelmawla describes a vision system used to measure and inspect various types of screw threads and their properties. Six computer vision algorithms were created to analyse captured images and then perform the measurement and inspection processes (Gadelmawla, 2017). Peng et al. (2016) presented computer vision's detection algorithms, which include an accurate measurement technique for internal/sectional diameter and a classification algorithm for surface defects, to maintain the quality of O-rings. In order to compare the phase-based optical flow approach with the digital image correlation (DIC) methodology, two sets of field tests were carried out in order to assess structural deformations on bridges (Ghyabi et al., 2023). Unlike the phase-based optical flow approach, the proposed approach employing Harris corner detection is computationally economical, rapid, generates rich feature information even on big images, and detects corners accurately even in noisy images.

Most of the researchers have used high-end cameras such as CCD, CMOS (DSLRs), stereovision-based cameras, etc. Many of these devices are quite expensive. The novelty of the present work is to use a low-cost smartphone, which is ubiquitous. The second distinct advantage of the present work is that it uses CV for metrological measurements in industry. This application is also novel to the present work. Moreover, because of smartphones' ease of use, it does not require much setup for the dimension measurement application.

Therefore, the proposed study explores the accessibility of routine equipment (a smartphone camera) while presenting a simple image processing technique that can be used to measure the dimensional parameters of components, parts, and specimens with less than 1% error for various industrial applications (machine industry, etc.). Further, it analyses the ease of dimension measurement using vision systems in automated manufacturing systems. The presented study utilizes the Harris-corner detection method to identify the corners of a specimen in an image. Subsequently, the dimension of the object is obtained by calculating the distances between these detected corners.

The paper is structured as follows: Section 2 explains the methodology employed to measure the dimensions of the parts, including image acquisition, an overview of the Harris-corner detection method, and calibration of dimensions using standard units. Section 3 focuses on the experimental setup and provides detailed specifications of the equipment used. In Section 4, different factors that impact the technique are discussed, and the results are summarized. Lastly, Section 5 presents the study's conclusion and outlines future prospects.

2. Methodology

The methodology is mainly divided into three parts: a) Taking the specimen picture from a fixed distance; b) Detecting the corners in the image; and c) Calibrating the detected corners to measure the dimension in standard units.

2.1 Image Acquisition

One of the key factors that influences measuring performance in computer vision is the approach by which clear images are obtained optimally and consistently. That is, if the acquired image is distorted or blurred, a significant amount of information referring to the contour data to be measured may be lost which makes stable results difficult to obtain. There are other considerable factors, such as the distance of the camera from the object, the height of the camera from the ground, the light intensity in the region, and other noises in the captured image. The image acquisition task consists of optically imaging the target object's characteristic information and converting the optical signal into image data (Shirmohammadi and Ferrero, 2014; Li, 2018b).

As discussed by Sutton (2013), modern cameras with sensor planes containing either a charge-coupled device (CCD) array or a complementary metal oxide sensor (CMOS) array was used for data acquisition. It also necessitates the use of standard lighting, such as modern, low-heat light emitting diode arrays or fibre-optic systems, which increases the cost as well as the complexity of the system. Compared to this, we used a smartphone camera with a CCD array-based sensor for image acquisition.

Table 1. List of symbols/variables.

p	Pixel value
x, y	2-Dimensional coordinate axis
u, v	Direction shifts in x and y coordinates
E	Sum of all the sum squared differences (SSD)
I	Intensity of the pixel
I_x , I_y	Partial derivatives of I
w	Window function
M	Structure tensor
R	Harris-Response/Score
λ_1 , λ_2	Eigen-values of M
D_g	Global metric coordinates (mm)
D_P	Local pixel distance (pixel)
K	Global distance per unit pixel (mm/pixel)

Table 1 describes the list of various variables and symbols used in the methodology.

2.2 Corner Detection

Edge and corner detection encompasses pre-processing an image for analysis. It detects changes in pixel intensity and distinguishes the corner points with respect to the background to measure the various length parameters. To measure the size and detect the corners of the specimen, clear surface features and an edge profile are required. The accuracy of dimensional measurements is directly related to the accuracy of edge detection. People have conducted a great deal of research on this, so many methods for detecting corners and edges have been developed (Peng et al., 2016).

In the current study, the Harris-corner detection method is applied to detect the corners of the specimen in the captured image. The Harris-corner method identifies points based on intensity variation in a local neighbourhood, which means that a small region surrounding the feature should show a large intensity change with shifting of the window in any direction (Sánchez et al., 2018).

Chris Harris and Mike Stephens made an early attempt to find these corners in their paper (Harris and Stephens, 1988). In 1988, Harris introduced a Combined Corner and Edge Detector, which is currently known as the Harris Corner Detector. The Harris corner detection algorithm is based on signal-point feature extraction. It causes the window (usually a rectangular area) to move infinitesimally in almost any direction (Sun, 2020).

It considers a small window that surrounds each pixel (*p*) in the image. The motive is to locate the unique pixel windows through this image. By slightly moving each window in a specific direction and seeing the amount of change in pixel values, this distinctiveness can be assessed. A simplistic mathematical tool is presented that determines the intensity difference for a shift of *(u, v)* across all directions.

Let us specify *E* (*u*, *v*) as the sum of all the sum squared differences (SSD), where u, v is the directional shift in *x* and *y* coordinates respectively for each pixel of window and *I* is the pixel's intensity value.

$$E(u, v) = \sum w(x, y)\,[I(x + u, y + v) - I(x, y)]^2 \tag{1}$$

here, *w(x, y)* denotes the window function.

The image's features are all pixels with larger *E* (*u*, *v*) values, as defined by some threshold limit. For corner detection, we must maximize this function *E* (*u*, *v*). This implies that we must maximize the second term in Eq. (1). The following equation results from applying Taylor expansion to the Eq. (1) and a few mathematical operations,

$$E(u, v) \approx [u \quad v] \left(\sum \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}\right) \begin{bmatrix} u \\ v \end{bmatrix}.$$

where, $M = \sum w(x, y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$.

So, $$E(u, v) \approx [u \quad v] \; M \begin{bmatrix} u \\ v \end{bmatrix} \tag{2}$$

Large value of SSD is required for all eight directional shifts of window, or it should be small for each direction. By solving for the eigen-vectors of *M* in Eq. (2), the directions for both the biggest and smallest increase in SSD can be obtained and the actual value of the increased amount can be figured out from the corresponding eigen-values. Using this, each window gets a score *R* as indicated in Eq. (3),

$$R = det(M) - k(trace\ M)^2 \tag{3}$$

and, $det(M) = \lambda_1 \lambda_2$ and $trace(M) = \lambda_1 + \lambda_2$.

λ_1 and λ_2 are the eigen-values of *M* and these eigen-values only decide whether a region is a corner, edge or flat.

The region is flat when $|R|$ is small, which occurs when λ_1 and λ_2 are small.
The region is an edge when $R < 0$, which occurs when $\lambda_1 >> \lambda_2$ or vice versa.
The region is a corner when *R* is large, which happens when λ_1 and λ_2 are big and $\lambda_1 \sim \lambda_2$.

2.3 Calibration

As we know, the size relationship of the target object is recorded in pixels using the acquired digital image. In order to determine the object's precise geometric dimensions, the relationship between the locations of each point in the real world and the pixels in the image must be established.

The pixel position is identified in the x and y coordinates of the pixel value and is mapped into the displacement in millimetres.

These coordinates were then converted into global metric coordinates by pixel calibration using Equation (4),

$$D_g = K \times D_p \tag{4}$$

where, D_g is the distance in pixels in global metric coordinates (mm), D_p is the local pixel distance (pixel), and K is the global distance per unit pixel (mm/pixel).

3. Experimental Set-up

The experiment is carried out by employing a Samsung Galaxy F62 smartphone camera equipped with 64 MP, a 1/1.73" sensor size, 0.8 micrometres of pixel size, phase detection auto-focused (PDAF), f/1.8 (aperture of the camera lens), and a 26 mm (wide) lens. Throughout the experiment, images of the parts were captured at a resolution of 2160 x 3840 with the full-screen feature of the smartphone, and the height of the smartphone from the ground was kept constant at 106 cm. To prevent unnecessary motion and noise, the smartphone is mounted on a tripod, and the measuring tape is used to precisely measure the distance between the smartphone and the object. Experiments were performed in the lab by keeping the plane surface behind the components to minimise the various intensity noise factors in the image in order to enhance the feasibility of the method proposed in this paper. The input data used for the analysis can be obtained from the following link: *https://cloud.iitmandi.ac.in/d/1186712da7774684b087/*.

The observations were made on the dimensional measurements of five different types of objects, which include a flat rectangular iron piece, an Allen-key/Hex key bolt, a hexagonal-headed bolt, and two screw bolts of different lengths shown in Figure 1 as Parts-(1-5) respectively.

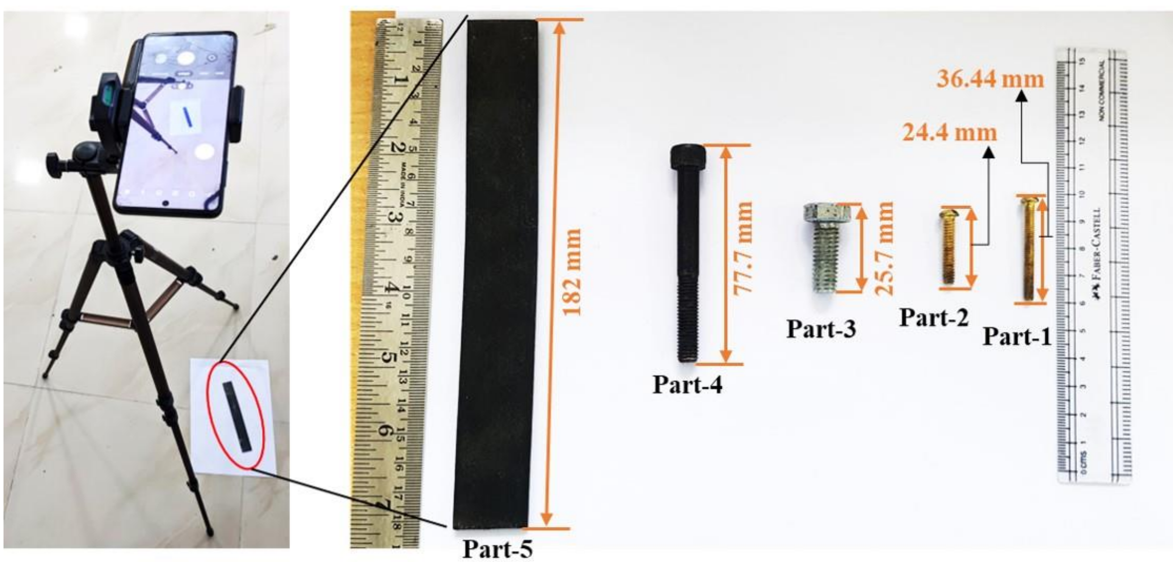

Figure 1. Experimental set-up: a) Smartphone camera mounted on tripod stand at a height of 106 cm from ground level and capturing the part-5 (object); b) Various parts/specimens used to validate the proposed technique.

The image processing parts comprised of cropping the image and detecting the corners. Python programming employing Spyder was used to acquire the image data, and libraries such as computer vision

(CV) and NumPy were used. Images were cropped to focus on the region where the specimen exists, which also reduces the noise in the image. Using the corner detection algorithm, features (corners of the parts) were located through all the experimental images, and the location of the detected point was calibrated to find the dimension in standard units.

4. Results and Discussion

The corners detected for the various parts are shown in Figure 2 by the red-coloured marks. The distance between the detected corners was measured using the distance formula, which was then calibrated into standard units. The measurement resulted in a calibration conversion ratio of 223.6-pixel units equal to 36.44 mm using the dimension of Part-1 as a reference value, as shown in Figure 2. The actual dimensions of the specimen are calculated by implementing the calibration factor in Eq. (4). As the camera's distance from the target object remains fixed throughout the experiment, the calibration factor used to calculate the dimensions of other objects/specimens also remains constant.

The caption for each part in Figure 2 depicts the longest length of a part measured with a Vernier calliper with a tolerance of 0.01 mm.

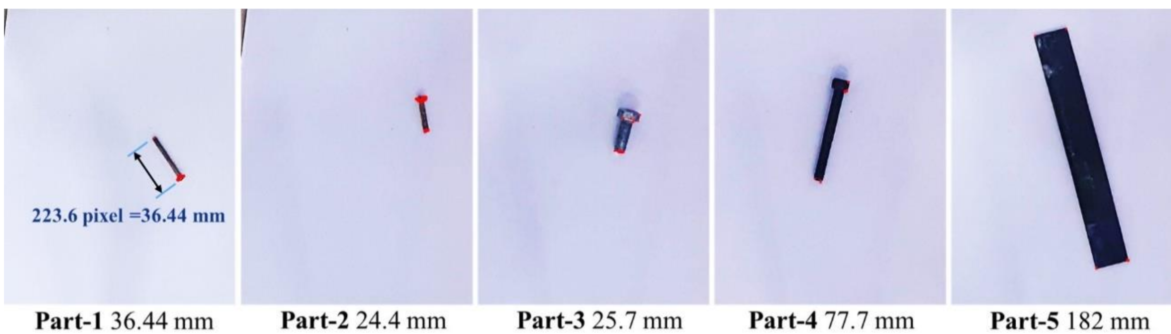

Figure 2. Representation of detected corner points (red dot marked) using CV technique for different parts.

Table 2 compares the dimensional measurements obtained using the Vernier calliper and the computer vision technique. The length of the parts is measured with 98% accuracy in all cases. Moreover, in the case of Part-4 bolt head length, threaded part length could also have been measured. Similarly, the width of the specimen was measured for the relatively large component size (Part-5).

Table 2. Comparison between the results obtained using CV technique and Vernier calliper measurement.

Part Characteristics	Vernier Calliper (Units in mm)	Computer vision (Units in mm)	Accuracy (%)
Part-1 (Length)	36.44	36.71	99.25906
Part-2 (Length)	24.4	24.69	98.81148
Part-3 (Length)	25.7	25.81	99.57198
Part-4 (Bolt head length)	7.64	7.76	98.42932
Part-4 (Length)	77.7	79	98.3269
Part-4 (Threaded length)	70.06	71.7	97.65915
Part-5 (Length)	182	185.27	98.2033
Part-5 (Width)	25.6	25.8	99.21875

The most basic segmentation process is object/background discrimination, which involves transforming the grey-level object in the image into a black object and the grey-level background into a bright background.

Because of their dimensionality reduction, binary images are widely used in many computer vision applications (Leta et al., 2006). Based upon this, a grey-scale conversion of the image has been done to implement corner detection, which also reduces the processing time.

It has been observed that by varying the gaussian filter size over the image data, the number of detected corners could increase to obtain more information about the contour of the part. This can also help in analysing the various important visible parameters of any specimen in an image. Based upon the user requirements, these parameters can be the dimensional length of any visible parameter such as width, diagonal length, length of tapered bar, etc. This is achieved by applying the distance formula between the detected points (coordinates) of the 2D image. It implies that the proposed technique can also interpret more information about a part by applying a minimum alteration in the detection technique as compared to the method used by Gadelmawla (2017), where they used a motivated CCD colour video camera with a set of lenses with different focal lengths to obtain the thread specification.

In correlation to the Vernier calliper measurement, the proposed method has an average accuracy of 98.7% for different types of specimens, indicating a better method to implement for industrial applications.

5. Conclusions

A unique approach is proposed for measuring the dimensions of various components based on computer vision techniques using a smartphone camera.

As the vision-based measurement technique is becoming widely attractive in the industrial manufacturing process and the existing measurement methods are so reliant on the operator. It also aims to lessen the various human errors that might take place due to the operators' poor efficiency and ineffective quality assurance. Therefore, it is essential to raise the manufacturing industry’s technological level in order to explore automated measurement systems for the dimension measurement of components with low cost, good precision, and high efficiency.

We outlined the image processing technique and presented evidence for eight different cases, obtaining the dimensions of five different parts with more than 98% accuracy. For the dimension measurement, the proposed method obtains a good corner feature extraction using Harris-corners and achieves a suitable precision for sorting the parts in an industrial chain. To implement the industrial requirements, it necessitates the development of better computational methods as well as structured improvements in the technique. As deep learning algorithms have revolutionized computer vision and can learn complex patterns and features in images, so, the deep learning algorithms are expected to play greater role in the future of dimensional measurement.

The advancements in the presented computer vision techniques can enable the creation of additional real-time dimensional measurement solutions that can be further integrated with the existing systems. In the future, more integration between computer vision-based dimensional measurement and robotics can lead to automated and efficient measurement processes.

Conflicts of Interest

The author declares that there are no competing interests.

Acknowledgements

The authors sincerely thank the acoustics and vibration laboratory at the Indian Institute of Technology, Mandi, for research infrastructure and for financial support HTRA fellowship provided by ministry of education.

References

Alonso, V., Dacal-Nieto, A., Barreto, L., Amaral, A., & Rivero, E. (2019). Industry 4.0 implications in machine vision metrology: An overview. *Procedia Manufacturing*, *41*, 359-366. https://doi.org/10.1016/j.promfg.2019.09.020.

Chen, P., Chen, F., Han, Y., & Zhang, Z. (2014). Sub-pixel dimensional measurement with Logistic edge model. *Optik*, *125*(9), 2076-2080. https://doi.org/10.1016/j.ijleo.2013.10.020.

Flugge, J., Wendt, K., Danzebrink, H., & Abou-zeid, A. (2002). Optical methods for dimensional metrology in production engineering. *CIRP Annals*, *51*(2), 685-699. https://doi.org/https://doi.org/10.1016/S0007-8506(07)61707-7.

Gadelmawla, E.S. (2017). Computer vision algorithms for measurement and inspection of external screw threads. *Measurement: Journal of the International Measurement Confederation*, *100*, 36-49. https://doi.org/10.1016/j.measurement.2016.12.034.

Ghyabi, M., Timber, L.C., Jahangiri, G., Lattanzi, D., Shenton III, H.W., Chajes, M.J., & Head, M.H. (2023). Vision-based measurements to quantify bridge deformations. *Journal of Bridge Engineering*, *28*(1), 05022010. https://doi.org/10.1061/(asce)be.1943-5592.0001960.

Gomes, J.F.S., & Leta, F.R. (2012). Applications of computer vision techniques in the agriculture and food industry: A review. *European Food Research and Technology*, *235*, 989-1000. https://doi.org/10.1007/s00217-012-1844-2.

Harris, C., & Stephens, M. (1988). A combined corner and edge detector. In *Alvey Vision Conference* (Vol. 15, No. 50, pp. 10-5244). https://doi.org/10.5244/C.2.23.

Hashmi, A.W., Mali, H.S., Meena, A., Khilji, I.A., & Hashmi, M.F. (2022). Machine vision for the measurement of machining parameters: A review. *Materials Today: Proceedings*, *56*, 1939-1946. https://doi.org/10.1016/j.matpr.2021.11.271.

Leta, F.R., Feliciano, F.F., de Souza, I.L., & Cataldo, E. (2006). Discussing accuracy in an automatic measurement system using computer vision techniques. *ABCM Symposium Series in Mechatronics*, *2*, 645-652.

Li, B. (2018a). Application of machine vision technology in geometric dimension measurement of small parts. *EURASIP Journal on Image and Video Processing*, *2018*, 1-8. https://doi.org/10.1186/s13640-018-0364-9.

Li, B. (2018b). Research on geometric dimension measurement system of shaft parts based on machine vision. *Eurasip Journal on Image and Video Processing*, *2018*. 108. https://doi.org/10.1186/s13640-018-0339-x.

Li, Z., Guo, R., Li, M., Chen, Y., & Li, G. (2020). A review of computer vision technologies for plant phenotyping. *Computers and Electronics in Agriculture*, *176*, 105672. https://doi.org/10.1016/j.compag.2020.105672.

Peng, G., Zhang, Z., & Li, W. (2016). Computer vision algorithm for measurement and inspection of O-rings. *Measurement*, *94*, 828-836. https://doi.org/10.1016/j.measurement.2016.09.012.

Sánchez, J., Monzón, N., & Salgado, A. (2018). An analysis and implementation of the harris corner detector. *Image Processing On Line*, *8*, 305-328. https://doi.org/10.5201/ipol.2018.229.

Shirmohammadi, S., & Ferrero, A. (2014). Camera as the instrument: The rising trend of vision based measurement. *IEEE Instrumentation & Measurement Magazine*, *17*(3), 41-47. https://doi.org/10.1109/MIM.2014.6825388.

Sun, Q. (2020). An improved harris corner detection algorithm. *Lecture Notes in Electrical Engineering*, *516*(1), 105-110. https://doi.org/10.1007/978-981-13-6504-1_14.

Sutton, M.A. (2013). Computer vision-based, noncontacting deformation measurements in mechanics: A generational transformation. *Applied Mechanics Reviews*, *65*(5), 050802. https://doi.org/10.1115/1.4024984.

Veeraraghavan, H., Masoud, O., & Papanikolopoulos, N.P. (2003). Computer vision algorithms for intersection monitoring. *IEEE Transactions on Intelligent Transportation Systems*, *4*(2), 78-89. https://doi.org/10.1109/TITS.2003.821212.

Wang, L., & Alexander, C.A. (2016). Additive manufacturing and big data. *International Journal of Mathematical, Engineering and Management Sciences*, *1*(3), 107-121. https://doi.org/10.33889/ijmems.2016.1.3-012.

White, D.J., Svellingen, C., & Strachan, N.J. (2006). Automated measurement of species and length of fish by computer vision. *Fisheries Research*, *80*(2-3), 203-210. https://doi.org/10.1016/j.fishres.2006.04.009.

Zheng, C., Sun, D.W., & Zheng, L. (2006). Recent applications of image texture for evaluation of food qualities—a review. *Trends in Food Science & Technology*, *17*(3), 113-128. https://doi.org/10.1016/j.tifs.2005.11.006.