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A Machine Vision Based Automated Quality Control System for Product Dimensional Analysis

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Abstract

Quality control (QC) in manufacturing processes is critical to ensuring consumers receive products with proper functionality and reliability. Faulty products can lead to additional costs for the manufacturer and damage trust in a brand. A growing trend in QC is the use of machine vision (MV) systems because of their noncontact inspection, high repeatability, and relatively low cost. This paper presents a robust MV system developed to perform comparative dimensional inspection on diversely shaped samples, including additive manufacturing products. The algorithm used performs dimensional inspection on a base product considered to have acceptable dimensions. The perimeter, area, rectangularity, and circularity of the base product are determined using blob analysis on a calibrated camera. These parameters are then used as the standard with which to judge additional products. Each product following is similarly inspected and compared to the base product parameters. A likeness score is calculated for each product, which provides a single value tracking all parameter differences. Finally, the likeness score is considered on whether it is within a threshold, and the product is considered to be acceptable or defective. The proposed MV system has achieved satisfactory results, as discussed in the results section, that would allow it to serve as a dependable and accurate QC inspection system in industrial settings.

Keywords: Machine Vision; Quality Control; Dimensional Analysis; Digital Quality; Rectangularity; Circularity; Production; Manufacturing

1. Introduction

Quality control (QC) in manufacturing is defined as determining whether requirement specifications for a product are satisfied. It is essential to manufacturers success that their products achieve a desired quality level. The

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consequences for failing to meet product quality expectations could lead to difficulty in selling, damage consumers trust and outlook in a brand, and jeopardize public health and safety. Traditional forms of QC were entirely dependent on human inspection. However, human's inspection performance can depreciate during a shift due to fatigue and repetition. This may allow for minor errors to go unnoticed, and perhaps costly, non-trivial errors as well [1].

Today, technological advancements are shifting the tedious inspection work from humans to machines. Major leaps have already been made in hardware and software that have displaced much of the QC inspection work to machines. A leading technology facilitating in QC is Machine Vision (MV), an imaging-based technology which seeks to extract information from images to mimic human inspection. A common MV system uses at least one camera and a processing unit (a computer) to analyze images captured of a product. Several types of analyses may be performed on a product image, such as dimensional, surface, or color analysis. From each analysis, quantified data on a desired aspect of quality is outputted. Unlike humans, a MV system can provide constant performance for long hours of work at a relatively low cost. Furthermore, MV systems are often able to perform inspections in a fraction of a second, whereas a human may cause a significantly greater delay. This provides a major benefit to manufacturers seeking to maximize efficiency and consistency.

A common MV system task is assuring a product's actual geometric state is in compliance with the intended, in other words having it perform a dimensional analysis on a product of interest. Most systems performing this task capture images directly above a product with a camera, therefore capturing two-dimensional data for analysis. With these pixel inputs, a MV system's program can, for example, judge whether a product is in an acceptable tolerance for length, width, and surface area. The MV system proposed in this paper is designed to continuously inspect products in a production line based on the attributes of perimeter, area, circularity, and rectangularity. These four parameters are considered in judging the overall likeness a considered item has to a desired item. The MV system proposed offers robust inspection capabilities that are suitable for handling curved edges, rotations, and gaps in products. Furthermore, the system is highly adaptable, meaning extensive model training is not required. Test results from the system showed a high repeatability and accuracy in distinguishing product with different geometric structures.

The remaining sections in the paper are as follows. Section 2 provides an overview of related work in regard to dimensional analysis using MV systems. Section 3 presents the machine vision system developed in detail and elaborates on its abilities. Section 4 provides test results using the proposed system and discusses its findings. Section 5 concludes the paper and shares opportunities for future work on the system.

2. Brief Review on application of Machine Vision Systems for Dimensional Analysis

Numerous Machine Vision (MV) systems exists that are used for dimensional analysis in a broad range of applications. Devi et al. [2] contrived a MV system to inspect rice grains for size and quality. The system proposed uses Canny Edge Detection to obtain rice grain contours, and then develops a region of interest around the contour. The extracted features using the system are area, length, breadth, and diagonal, which were used to classify rice types at a 90% accuracy. Further contributing to quality inspection of rice is Chen et al. [3] that identified broken, chalky, and damaged or spotted rice grains. A unique algorithm was developed for each defect with the former two using support vector machines and the latter using Sobel gradient operator and Otsu segmentation. The reported defect identification accuracies were 99.3%, 96.3%, and 93.6%, respectively.

Kazemian et al. [4] designed a MV system to inspect large-scale additive manufacturing (LSAM) extrusion in real-time. LSAM uses building materials, such as cement, to print buildings and other types of structures. The material quality is paramount to ensuring safe and long-standing shelters are created. MV is used here to create a closed-loop inspection system that determines a LSAM's extrusion rate and make adjustments if needed. Since the extruded material in this system is seen from atop, the system perceives a thick line whose width is used to identify extrusion rate deviations. Test results demonstrated correction capabilities within ±10% of the desired rate in less than three seconds.

An advantage of using MV systems is the increase in inspection speed. Huang et al. [5] improved inspections on glass bottle breakage and contamination detection with no loss in observation time. The system developed uses a radial scanning method followed by contour fitting to identify breakage on bottles mouths. Bottles with damaged bottoms were detected using a Blob algorithm. The system accomplished an inspection rate of 72,000 bottles per hour while detecting 100% of defective bottles and mislabeling 0.297% of bottles. Zhang et al. [6] created a MV system to inspect spring clamps based on inner diameter, length of cut, and cut angle. The algorithm uses two polar to circular transformations along with fitting inner circles and lines to determine feature data. The system does not use any template matching traditionally used in MV. Experimental results showed inspection rates of 0.5 s per piece and an overall system precision of 100%.

Moru and Borro [7] utilized high accuracy equipment to develop a MV application for subpixel gear inspection. The system uses a telecentric lens with a low calibration error of 0.06 pixel. Additionally, a low tolerance of ±0.02 mm was set to improve quality control inspection. Three algorithms were developed for the inspection that check on inner diameter, outer diameter, and number of teeth. Ultimately, the system labeled all 12 of the tested gears correctly given the specified tolerance and computed uncertainty.

This paper builds off goals and algorithms aforementioned. It was essential the proposed system achieve high levels of accuracy and precision as the applications mentioned. Additionally, the system performs at a high inspection rate like the glass bottle inspection [5] and clang inspection [6]. Finally, the system offered is robust in that it can inspect various complex shapes with just inspection of a desired object. This makes practical use simple, flexible, and non-time consuming.

3. Proposed Machine Vision System Developed

The developed MV system consists of a 5MP, CMOS industrial camera made by Hikvision, a circular LED light source, and a metal rig provided by Dobot® (Figure 1). Image processing is performed on the Dobot Vision Studio application which provides a simple interface to operate on and organized feedback on data processed. The algorithm used in the proposed MV system compares the dimensional likeness of similar products (i.e. products of the same geometric shapes). An overview of the algorithm (Figure 2) is provided:

1. First, perform an inspection on an exemplar object known to meet the desired design specifications.
2. Store parameter data from the qualified object for future comparison.
3. Iterate a loop indefinitely, or a specified number of times, with each iteration performing an inspection on a new object. The data collected from each new object is compared to the initial object and given a percent rating on its likeness to the initial object. A new object is considered acceptable if it lies within a specified tolerance.

Fig. 1. Machine Vision System.

The dimensional inspection process is currently designed to analyze the surface of an object from a top view. This process is considered robust for its handling of complex shapes and geometries. Examples of shapes capable of analysis are sinusoidal objects, gapped objects, and objects with varying edge patterns. The dimensional inspection process performs a blob analysis which extracts the contour of a surface in an image [8]. The blob analysis uses a single threshold mode, a light blob to dark background polarity, and a minimum object pore area of 100 pixels in a 1600 x 1600 image. The object under inspection can be placed anywhere within the area captured in an image and can be rotated any degree about an axis orthogonal to the base and camera. No loss in accuracy results from these translations and rotations. Additionally, the average run time for the proposed algorithm is 266 ms per item after the delay for object replacement has been removed, which improves upon the speeds of the 0.5 s time in the work by Zhang et al [6]. Using a calibrated camera, the system can output the physical distance of a surface's perimeter and area. Therefore, if an object known to meet the desired physical design specifications is available, it can serve as the initial object for the algorithm considered. If no initial object is available, the expected parameter values can be manually inputted. The algorithm provides a strong comparison of how a set of products appears relative to a base.

Four parameters are considered in the algorithm's likeness scoring: 1) perimeter, 2) area, 3) rectangularity, and 4) circularity. The perimeter is measured as the number of pixels in an object's outline. Similarly, area is measured as the number of pixels contained in an object. Rectangularity measures the area filled by the object over the area filled by the smallest circumscribed rectangle containing the object and outputs a value from 0 to 1, where 1 is a pure rectangle. Likewise, circularity measures the area filled by the object over the area filled by the smallest circumscribed circle containing the object and outputs a value from 0 to 1, where 1 is a pure circle.

These four parameters can simultaneously be measured and are expressed in the likeness score as follows:

$$L = aP + bA + cR + dC$$

Where; a, b, c, and d, are weights assigned to prioritize parameter values. P, A, R, and C are respectively, the perimeter, area, rectangularity, and circularity. These values are calculated with:

$$X = 1 - \frac{|x_{new} - x_{initial}|}{x_{initial}}$$

Where, x_{new} can be substituted with a parameter from a product being compared and $x_{initial}$ can be substituted with a parameter from a desired product. Finally, the MV system determines whether a product inspected should be accepted or rejected based on product geometrical similarity. This decision is based on a predetermined threshold that can be altered to be highly selective or more tolerable model.

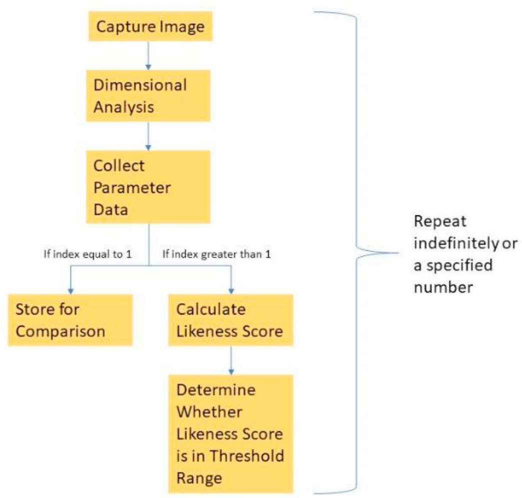

Fig. 2. Proposed Machine Vision Algorithm for Product Dimensional Analysis.

A step-by-step process flow of the algorithm is provided here:

1. Capture an image of an initial item that best meets the quality requirements.
2. Perform dimensional analysis on the image in step 1.
3. Store parameter data values for future comparison use.
4. Capture image of new item.
5. Perform dimensional analysis on image from step 4.
6. Using parameter data in step 5, calculate likeness score for an item.
7. Check if likeness score is within threshold range. Output result for proper item handling.
8. Repeat steps 4-7 a desired number of iterations.

4. Initial Test Results and Discussion

4.1. Common Shapes

To test the performance of the proposed MV system, three common shapes were used: cubes, cylinders, and sinusoids (Figure 3). The items tested were printed using MakerBot 3D printers, which allowed for rapid dimensional alterations. Data collected from several cube test comparisons is shown in Table 1. The base items are those that would be test standards and the tested are those compared to the base. As shown in Table 1, the likeness scores obtained when comparing two dimensionally different objects are low. Furthermore, when observing the likeness scores of dimensionally equal objects, a perfect or near-perfect likeness score is obtained.

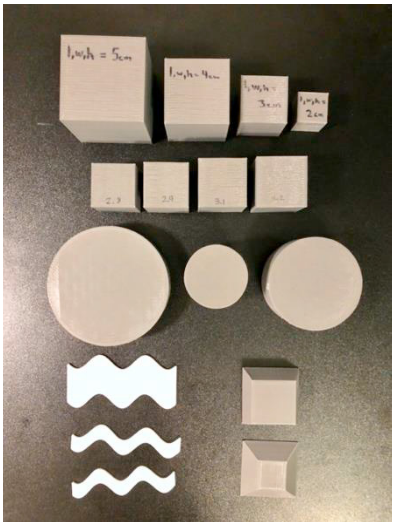

Fig. 3. Shapes Used for Testing.

Table 1: Cube Test Comparison

Shape	Base	Tested	Likeness Score
Cube	5 cm	5 cm	1.000
Cube	5 cm	4 cm	0.794
Cube	4 cm	3 cm	0.740
Cube	3 cm	2 cm	0.678
Cube	2 cm	2 cm	0.999

An example of the full data used to calculate the likeness score for base 4 cm and tested 3 cm in Table 1 is shown in Table 2. Note that the values shown in the table are in pixels and have not been converted to distance. Additionally, the coefficients a, b, c, and d used for the likeness score are 0.4, 0.4, 0.1, and 0.1, respectively. These values were selected in order to prioritize perimeter and area in making a quality decision. In the case that an item contains the same perimeter and area but not shape as an intended item, the rectangularity and circularity scores can flag this unique instance.

Table 2: Test Case Data

Item	Area	Perimeter	Circularity	Rectangularity
Cube 4 cm	173503.000	1780.497	0.647	0.985
Cube 3 cm	92641.000	1297.453	0.638	0.984

Data on the tests performed for cylinders and sinusoids is provided in Table 3 and Table 4. In Table 3, r is the radius of the cylinder and h is the height of the cylinder. In Table 4, l is the length of the sinusoid and w is the width of the sinusoid.

Table 3: Cylinder Test Comparison

Shape	Base	Tested	Likeness Score
Cylinder	r = 4 cm, h = 2 cm	r = 4 cm, h = 2 cm	0.999
Cylinder	r = 4 cm, h = 2 cm	r = 3 cm, h = 3 cm	0.771
Cylinder	r = 3 cm, h = 3 cm	r = 3 cm, h = 3 cm	0.999
Cylinder	r = 3 cm, h = 3 cm	r = 2 cm, h = 4 cm	0.701
Cylinder	r = 2 cm, h = 4 cm	r = 2 cm, h = 4 cm	0.999

Table 4: Sinusoid Test Comparison

Shape	Base	Tested	Likeness Score
Sinusoid	l = 1 cm, w = 7.5 cm	l = 1 cm, w = 7.5 cm	0.995
Sinusoid	l = 1 cm, w = 7.5 cm	l = 0.8 cm, w = 7.1 cm	0.099
Sinusoid	l = 1 cm, w = 7.5 cm	l = 2.5 cm, w = 7.5 cm	0.948

4.2. Complex Geometrical Shapes

A complex geometrical shape inspection was performed to demonstrate the proposed MV system's capabilities. The complex shape used contains a single point edge, a squared-bumps edge, a circular-bumps edge, and a triangular-bumps edge. Figure 4 shows the image results of the inspection between a base complex part with a 7 cm inner square reaching each corner and the base part shrunken by 95%. Additional inspections and data are provided in Table 5, showing how the system performed with the same base part against an alike part and an enlarged part.

Table 5: Sinusoid Test Comparison

Shape	Base	Tested	Likeness Score
Complex Part	Inner square = 7 cm	Inner square = 7 cm	0.996
Complex Part	Inner square = 7 cm	Base shape • 0.95	0.948
Complex Part	Inner square = 7 cm	Base shape • 1.05	0.949

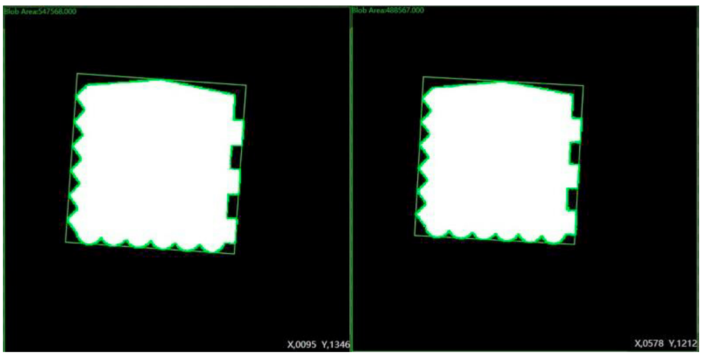

Fig. 4. (a) Original Complex Part; (b) Complex Part Shrunken to 95%.

4.3. Frustums

Although the MV system proposed performs well for items with entirely uniform cross-sections, the system at its current stage is unable to properly inspect items that have varying cross-sections. An example of this shortcoming is the frustrum shape, which is similar to a pyramid that has had its upper section sliced. The inspection system misidentifies the top surface with the larger bottom surface, therefore reports incorrect data.

4.4. System Accuracy

In order to demonstrate the inspection capabilities of the proposed system, a test was performed using four cubes with slightly varying dimensions to the base. The base cube's sides are 3 cm, while the tested cubes have sides of 2.8 cm, 2.9 cm, 3.1 cm, and 3.2 cm. The test results are shown in Table 6 and the blob analysis for the tested 3.1 cm cube is shown in Figure 5. The likeness scores in Table 6 demonstrates the system's capacity to identify minor defects just a fraction of a centimeter. In application, a high likeness score threshold can be set to avoid even minor dimensional deviations.

Table 6: Cube Test with Minor Dimensional Changes

Shape	Base	Tested	Likeness Score
Cube	3 cm	3 cm	1.000
Cube	3 cm	2.8 cm	0.924
Cube	3 cm	2.9 cm	0.958
Cube	3 cm	3.1 cm	0.958
Cube	3 cm	3.2 cm	0.923

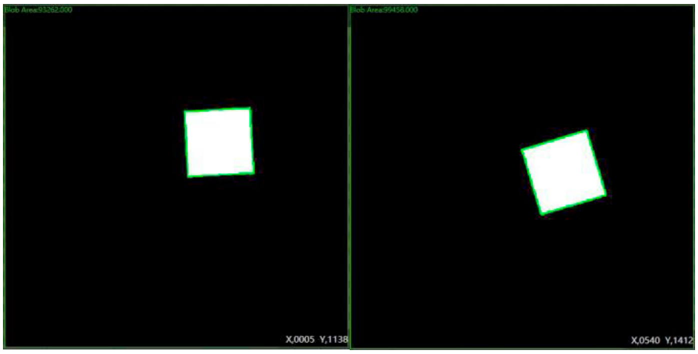

Fig. 5. (a) Dimensional Analysis 3 cm Cube; (b) Dimensional Analysis 3.1 cm Cube.

5. Conclusion

Quality control is a critical issue in all industries that MV systems are assisting in. The MV system proposed in this paper offers a simple setup capable of identifying defects in diverse shapes. As shown, the system could identify defects in cubes, cylinders, and sinusoidal objects. These shapes makeup many industrial products, therefore making the use of such systems relevant and necessary. Furthermore, it is essential that effective MV systems identify minute defects in objects. The proposed system was able to identify millimeter sized defects making its use practical. Future work will be done on enhancing the degree defects can be detected to beyond the millimeter scale, allow the system to perform inspections on objects with non-uniform cross-sectional areas, challenge the level the system can consistently report at, and study how varying the likeness score coefficients affects the system's performance.

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