Inspecting spring clamp dimensions with machine vision

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Abstract. The reliability of spring performance, particularly the reproducibility of spring dimensions, plays a vital role in quality control of springs. In this paper, we develop a spring clamp inspection system that uses machine vision and can be used to inspect the important dimensions of a spring clamp. The proposed inspection algorithm can be used to determine the dimensions of a spring clamp without input training samples, regardless of the orientation of the spring. This is in contrast to a traditional machine vision system that uses a template matching algorithm. The experimental results show that the precision of the proposed machine vision-based system is 100%, and the measurement time is less than 0.5 s for a single piece.

1. Introduction

Springs are important parts that are widely applied in machinery [1]. The reliability of spring performance, particularly the reproducibility of spring dimensions, plays a vital role in quality control of springs.

A spring clamp is a typical spring that is widely used to fix other machinery components. Figure 1 shows various specifications of a spring clamp: \( d_{\text{inner}} \) is the diameter of the spring inner circle, \( l_{\text{cut}} \) is the length of the cut, and \( \theta_{\text{cut}} \) is the cut angle.

In a spring factory, the spring clamp specifications, including \( d_{\text{inner}} \), \( l_{\text{cut}} \), \( \theta_{\text{cut}} \), are inspected by humans with a special tool. This reduces the evaluation accuracy, and the productivity ranges from approximately 30 to 40 pieces per minute.

Spring manufacturers call for complete inspection to ensure that all springs meet their standards. However, human inspection makes it impossible to get rid of all disqualified springs.

The production rate increases greatly as the technique is developed, which lowers the price for a spring piece, thus increasing profit. Meanwhile, machine vision has been developed over many years. Significant research has been conducted in this field [2], especially regarding basic industry components like bearings [3], gears [4], and screws [5]. However, the use of machine vision to inspect the dimensions of springs, especially spring clamps, is rarely reported. To the best of our knowledge, defects in clamp-like springs were examined using machine vision [6]. A machine vision-based inspection system for inspecting spring clamps is proposed in this paper. We designed a high efficiency lighting and image acquisition system, as shown in Figure 2. Then, a series of image processing methods is proposed for determining the dimensions of a spring clamp.
2. Lighting and image acquisition system

The time required for the machine vision system to inspect a spring should be less than 0.5 s in order to meet production requirements. This time frame should include machine movement, image acquisition, signal transmission, and inspection. A high efficiency lighting and image acquisition system is developed for inspection. This system, as shown in Figure 2, consists of a blue LED, a ring-shaped glass pane, a bi-telecentric lens and a camera. The camera a CCD with 2452×2056 pixels, where the size of each cell is $3.45 \times 3.45 \, \mu m^2$ and the size of each pixel is $15 \times 15 \, \mu m^2$. The image acquisition program and algorithm were implemented on a personal computer with an Intel® Core™ i5-4200H 2.80 GHz CPU.

A special spring vibration feeder transferred the springs onto a conveyor belt, and the springs were then transferred onto the ring-shaped glass pane shown in Figure 3. Meanwhile, the ring-shaped glass pane rotated around the center. The image was acquired when the spring moved across the image acquisition area, which were used to calculate the dimensions with our proposed inspection algorithm.
The results were used for three channel classification: G denotes “Good”, NG denotes “Not good”, and NS denotes “Not sure”.

3. Inspection algorithms

In order to determine the dimensions of a spring clamp, the center point of the spring must be determined first, followed by application of an initial polar to circular (P2C) transformation. The second P2C transformation is applied with the center point of inner circle, yield all the dimensions from the P2C transformed image. A flow chart for this algorithm is shown in Figure 4.

3.1. Image acquisition

The camera is triggered by software, and the acquired image is transferred to a PC with an Ethernet cable. The maximum transfer rate is 15 fps with full resolution. An acquired raw image is shown in Figure 5(a).

3.2. Binarization

Prior research has focused on edge and feature detection in images [7, 8]. As for the difference between the foreground and background in an image, threshold methods are used to segment springs from the background. Figure 5(a) shows that the difference between the foreground and background is obvious, thus we use Otsu thresholding method [9] to binarize the acquired image. The color of foreground and background are reversed for the convenience, as shown in Figure 5(b).

3.3. Center of gravity

The center of gravity of a spring in the binarized image can be determined using the following equation:

\[
\text{Row}_{\text{gu}} = \frac{\sum \sum B(i, j) \cdot j}{\sum \sum B(i, j)}, \quad i = 1, 2, 52, \quad j = 1, 2, 56, \quad 2056
\]  

(1)
Col_{gra} = \sum \sum B(i,j)*i, i = 1,2,\ldots,2452, j = 1,2,\ldots,2056 \tag{2}

where Row_{gra} and Col_{gra} are the row and column position of the center of gravity, respectively. Figure 5(b) shows the center of gravity marked with a red cross (‘+’); B(i,j) is the gray value of the binarized image at location (i,j).

Figure 5. Image processing methods.

3.4. First P2C transformation
A P2C transformation [10] is applied to the image in Figure 5(b), transforming the ring-shaped spring clamp into the rectangular belt shown in Figure 5(c). However, as the center of gravity is not the center of the ring-shaped spring clamp, the transformed image in Figure 5(c) is not a straight belt. A P2C transformation uses the following equations:

\begin{align}
x &= Col_{gra} + r \cdot \cos(\theta) \\
y &= Row_{gra} + r \cdot \sin(\theta)
\end{align} \tag{3,4}

where \( \theta = 2\pi w/W, r \in [0,r_{out} + N_p) \), (x, y) is a point before transformation, (w, r) is the corresponding point after the transformation, W is the transformed width, \( r_{out} \) is the estimated value of
spring outer circle radius, and $N_p$ is a constant that ensures the transformed image includes all the features of the spring clamp.

### 3.5. Fit inner circle

The upper edge of the white belt in Figure 5(c) corresponds to the inner circle of the spring clamp, where a set of points is used to fit an inner circle using least squares regression. Figure 5(e) shows the obtained points marked in red circles, and the fitted center of the inner circle $(oRow, oCol)$ is marked in blue.

### 3.6. Second P2C transformation

Another P2C transformation is applied to the image in Figure 5(b). However, the center point is replaced by the fitted circle of the inner center using the following equations:

$$x = oCol + r \cdot \cos(\theta)$$

$$y = oRow + r \cdot \sin(\theta)$$

where $r_{inner}$ is the estimated radius of the spring inner.

Figure 5(d) shows that a straight belt shape has been located. Most of the required parameters can be determined from this image.

#### 3.6.1. Length of cut $l_{cut}$

Points $(w_{\theta_i}, r_{\theta_i})$ and $(w_{\theta_i}, r_{\theta_i})$ in Figure 5(d) are on the left and right points of the outer circle cut of the spring clamp, respectively. The cut length $l_{cut}$ can be determined with the following equation:

$$l_{cut} = \sqrt{((x_i - x_j)^2 + (y_i - y_j)^2)}$$

where the points $(x_j, y_j)$ and $(x_j, y_j)$ correspond to $(w_{\theta_i}, r_{\theta_i})$ and $(w_{\theta_i}, r_{\theta_i})$ in Equations (5) and (6). The following can be determined from Equations (5), (6), and (7):

$$l_{cut} = \sqrt{((r_{\theta_i} \cdot \cos(\theta_i) - r_{\theta_i} \cdot \cos(\theta)) + r_{\theta_i} \cdot \sin(\theta_i) - r_{\theta_i} \cdot \sin(\theta_i))^2}$$

#### 3.6.2. Diameter of inner circle

In order to measure the maximum and minimum diameters across the inner circle, all the diameters across the inner circle center should be found out. Figure 5(d) shows that is required to calculate the diameter $d_{\theta_i}$ across $(w_{\theta_i}, r_{\theta_i})$, where the angular difference from $(w_{\theta_i}, r_{\theta_i})$ is $\pi$. Thus, the diameter $d_{\theta_i}$ can be determined using the following equation:

$$d_{\theta_i} = r_{\theta_i} + r_{\theta_i}$$

where $r_{\theta_i}$ and $r_{\theta_i}$ are the radius across $(w_{\theta_i}, r_{\theta_i})$ and $(w_{\theta_i}, r_{\theta_i})$, respectively. The yields the maximum and minimum diameters of the inner circle while avoiding the cut position.

### 3.7. Fit lines

Two sets of cut edges are required to determine the cut angle, as shown in Figure 5(d). These points will transfer into the points in Figure 5(b) via Equations (5) and (6). Least squares regression [11] is used to fit the two cut edge lines, yielding the direction vectors of the two lines $(1, k_1)$ and $(1, k_2)$. As the cut angle $\theta_{cut}$ is an acute angle, it can be calculated using the following equation:

$$\theta_{cut} = \tan^{-1}(\left| \frac{k_1 - k_2}{1 + k_1 \cdot k_2} \right|)$$
4. Experimental results

The inspection algorithm was programmed based on OpenCV using C++. Three sets of springs were collected to evaluate the proposed algorithm, as shown in Table 1. Testing set \( a \) includes 368 G and 8 NG testing samples; set \( b \) includes 452 G and 10 NG testing samples; set \( c \) includes 513 G samples and 1 NG sample. All testing samples were carefully collected from a leading spring clamp manufacturer in China. All the testing samples were classified as G and NG by several skilled human inspectors.

| Set | \( d_{\text{inner}} \) (mm) | \( l_{\text{cut}} \) (mm) | \( \theta_{\text{cut}} \) (degree) |
|-----|-----------------|-----------------|-----------------|
| \( a \) | 15.80_{-0.4} | 3.7±0.2 | 60±5 |
| \( b \) | 15.80_{-0.4} | 3.7±0.2 | 60±5 |
| \( c \) | 15.80_{-0.4} | 3.7±0.2 | 60±5 |

We compared results from the proposed machine vision-based inspection system with those from skilled human inspectors. Springs with all three parameters within tolerance, are denoted “Good” while the others are denoted “Not Good,” as indicated in Table 1. The results from the machine vision system and human inspection are shown in Tables 2 and 3, respectively. The precisions of the machine vision system for all 3 test sets are 100%. The time required to inspect one piece is less than 0.5 s. Meanwhile, the precision of human inspection for the three test sets are 99.46%, 99.56%, and 100%. This indicates that skilled human inspectors are not completely reliable, especially when they are working for a prolonged period of time. The time required for a skilled human inspector to inspect a single spring ranges from 1.6 to 2 s.

| Set | Good | Not Good | Number of samples | Total inspection time (s) | Precision |
|-----|------|----------|-------------------|--------------------------|-----------|
| \( a \) | 368  | 8        | 376               | 173                      | 100%      |
| \( b \) | 452  | 10       | 462               | 211                      | 100%      |
| \( c \) | 513  | 1        | 514               | 242                      | 100%      |

| Set | Good | Not Good | Number of samples | Total inspection time (s) | Precision |
|-----|------|----------|-------------------|--------------------------|-----------|
| \( a \) | 370  | 6        | 376               | 652                      | 99.46%    |
| \( b \) | 450  | 12       | 462               | 786                      | 99.56%    |
| \( c \) | 513  | 1        | 514               | 847                      | 100%      |
5. Conclusions
This paper presents a machine vision system for inspecting the dimensions of spring clamps. The experimental results show that the inspection precision and efficiency provided by the machine vision-based system are superior to that provided by human inspection.

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