An Effective Coaxiality Measurement for Twist Drill Based on Line Structured Light Sensor

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Abstract—Aiming at the accurate and effective coaxiality measurement of twist drills with irregular surface, an optical measurement mechanism is proposed in this article. First, a high-precision rotation instrument based on four core units is designed, which can obtain 3-D point cloud data of twist drills at all angles. Second, in the data processing stage, an improved robust Gaussian mixture model is proposed for accurate and rapid blade back segmentation. To improve the measurement efficiency, a rapid reconstruction method of twist drill axis based on orthogonal synthesis is proposed, which can rapidly locate the maximum deviation between the actual axis and the reference by using the extracted blade back data. Finally, by calculating the maximum radial Euclidean distance from the benchmark, the coaxiality error of the twist drill is obtained. Compared with other measurement methods, the experimental results show that our proposed method performs well with high efficiency of less than 3 s/pc and the average measurement error is about 0.020 mm. The experimental results and uncertainty analysis show that the proposed method is effective and automatic and can be applied to the coaxiality measurement of twist drills of various specifications.

Index Terms—Coaxiality measurement, line structured light sensor, noncontact measurement, twist drill, unsupervised machine learning.

I. INTRODUCTION

TWIST drill is an important mechanical tool for drilling round holes in workpiece. It consists of a handle part and a working part, as shown in Fig. 1. As an important tolerance of the rotating body, the coaxiality directly affects the processing quality [1]. Twist drills with large coaxiality errors will cause hole size deviation and damage the machined workpiece. Therefore, in the intelligent manufacturing environment, it is of great significance to quickly and accurately measure the coaxiality error of twist drills.

Despite the rapid development of different measurement techniques, online precision measurement of complex surfaces is still facing challenging problems [2]. At present, common contact coaxiality measurement technologies include bearing gauge, coaxiality measurement instrument, and coordinate measuring machine (CMM) [3], [4], [5]. Among them, the CMM [6] equipped with a certain precision scanning probe can perform high-precision and robust measurements [2]. However, like other contact methods, due to the complicated operation and slow measurement process, it is difficult to be applied in automatic manufacturing scenarios.

With the rapid development of machine vision and optics [7], [8], [9], [10], [11], photoelectric technologies have become attractive in noncontact measurement methods. They can have a wide measurement range and dense sampling rate [2]. At present, noncontact optical measurement technologies can be divided into two categories: passive and active methods. Passive methods use stereo-vision techniques [12], [13] to reconstruct the 3-D topography of object surfaces without active illumination. However, due to the need to detect corresponding different images pairs, the measurement accuracy varies with the surface texture of the object. Time-of-flight (TOF) technologies [14] use the TOF of a signal to measure the distance between asynchronous transceivers (or reflected surfaces). The entire system can be very compact and suitable for mobile applications. However, this technology still suffers from low image resolution, high power consumption, and so on. The structured light technologies [15] actively project structured light with encoded information onto the surface of an object and reconstructs the object by decoding the information. Among them, image registration is a key step, which will affect the measurement accuracy. Based on triangulation or echo analysis, laser displacement sensors are a class of effective and practical sensors that have been widely used in geometric tolerance measurement [3], [16]. Chai et al. [3] used a laser displacement sensor to measure the coaxiality of composite gears by acquiring the profile of the cross section, separating the apex data of the gear, and fitting the center of the cross section. Pei et al. [16] applied a single laser...
displacement sensor to realize the radial jump measurement of gears and improved the measurement accuracy by optimizing the laser angle and installation position. Zhang et al. [17] used a laser displacement sensor to obtain the surface profile of the part and fit the center of the circle to calculate the concentricity of large forgings, thereby improving the operation precision of disassembly and assembly. However, since the laser displacement sensor is single-point scanning, it is difficult to achieve efficient measurement. Line structured light vision technologies are representative and demonstrate high accuracy and efficiency [18]. They can monitor the shape of objects by scanning and reconstructing normal section profiles [18] [19]. Wang et al. [20] adopted structured light vision to dynamically measure rail profile and propose a simple and effective distortion rectifying method to avoid rail profile distortion. Li et al. [21] developed a novel system based on structured light binocular vision to obtain the full profile of the rail and enable more accurate and efficient rail wear measurement on site. Shang et al. [22] adopted incoherent line structured light vision sensor to measure gear teeth by extracting tooth profiles. In addition, line structured light vision technology can achieve high-precision measurements by employing high-power lasers and high-resolution cameras [16], [22]. Furthermore, combined with a certain rotating structure, the measuring mechanism can be made very flexible and precise [23]. Inspired by this, a coaxiality measurement mechanism based on line structured light sensor is proposed to measure twist drills.

Even more, in addition to high-resolution data acquisition, precise measurement of dimensional microfeatures also needs tailor-made evaluation methods [24]. In the field of instrumentation and measurement, point clouds are one of the most primitive 3-D data representations that can accurately reflect the real size and shape structure of objects [25]. To obtain the data of the target area, segmentation or reconstruction of the dimensional measurement data is a crucial step. These methods can be divided into several categories, such as edge-based, region growing (RG), model-based (MB), attribute clustering, and hybrid approaches [24], [26], [27].

Edge-based methods perform segmentation by detecting different metrics on neighboring pixels and use them as transition zones between segmented elements. This method is fast but also very sensitive to noisy data [24], [27]. Region-growing methods combine adjacent pixel points with seed points according to certain criterion [25], but these methods tend to undersegment or oversegment [24], [25], [27]. Zhang et al. [25] proposed an RG method based on 2-D-3-D mutual projections, which divides the visible and occlusion points by selecting initial seed points with geometric information. Ma et al. [28] proposed a segmentation framework based on the RG method, including neighborhood search, filter sampling, and Euclidean clustering, which can improve the speed and accuracy of the algorithm. MB methods utilize geometric primitives (such as planes, spheres, or cylinders) to group measured points [24], [26]. This method is widely used for partitioning tasks in reverse engineering. Inspired by the MB ideas, Erdenebayar et al. [26] put forward flake surface recognition model that can remove noisy point clouds by resampling. Zhang et al. [29] presented to integrate normal-angle cues into discriminative feature learning to enhance the local structure representation of small objects. Attribute clustering methods include attribute computation and attribute-based clustering of point clouds. Either way, for complex surface measurement, any method needs the ability to automatically and optimally partition microfeature data with low uncertainty, so as to obtain a maximum number of acquisition points to associate with the corresponding geometric element [30]. It is turned out that hybrid approaches clearly have the potential to automatically optimize partitions [24]. Lübke et al. [30] demonstrated that automatic partitioning is less sensitive to the initial value of the approximation and can converge reliably; von Freyberg et al. [31] successfully applied automatic partitioning methods to micromeasurement evaluation. In addition, in [32], a statistical method was incorporated to automatically detect outliers. In the coaxiality measurement of the twist drill, the segmentation algorithm needs the ability to automatically partitioning acquired data with microchange of surface normal-angle cues of different geometric elements. Inspired by the above algorithms, an automated partitioning idea is integrated into the attribute clustering method. In this idea, a statistical method based on our improved Gaussian mixture model (GMM) is designed to learn discriminative features of geometric elements on twist drills. In our improved GMM model, local spatial neighboring information is introduced to enhance the microfeatures of each element such as blade back and blade groove and overcome the noise sensitivity of the classical GMM.

In summary, the motivation of this article is as follows. First, to improve the efficiency and accuracy of coaxiality measurement for twist drill, an effective measurement mechanism based on a line structured light sensor is proposed, which can obtain the full angle data of the twist drill. Second, due to the worthy development of unsupervised machine learning, GMM can be used to fit arbitrary probability density functions with strong approximation ability and high robustness [33]. It has been widely used in object inspection [33], background modeling [34], modeling segmentation models [35], [36], and so on. In order to accurately partition geometric elements of the twist drill and obtain measurement data of circular cross section for coaxiality calculation, a point cloud segmentation method based on improved GMM is proposed to learn the discriminative feature distribution of geometric elements. In addition, local (neighborhood) spatial information is introduced to overcome the sensitivity of classical GMM to noise. Third, to improve the efficiency, a rapid axis reconstruction method based on orthogonal synthesis is proposed to locate the maximum deviation of the actual axis from the benchmark. Finally, experimental results show that measurement time is less than 3 s/pc and the average measurement deviation is about 0.020 mm. The analysis of the measurement uncertainty demonstrates that the proposed method can be applied to the online measurement of twist drills of different specifications in practical scenarios. The main contributions are given as follows.
A 3-D coaxiality measurement mechanism for twist drills is proposed, which contains three core modules: three-rule system calibration, blade back extraction, and maximum deviation location and calculation of the axis. The proposed mechanism can acquire full angle 3-D data of the twist drill by rotation for precision measurement.

2) An improved GMM-based segmentation method is investigated to learn discriminative features of geometric elements and segment the point cloud data. Among them, local spatial information is introduced to overcome the sensitivity of the classical GMM to noise, and a two-level division strategy is designed to construct local neighborhood. Experiment results demonstrate that the investigated method is robust and accurate.

3) A rapid reconstruction method of actual axis based on orthogonal synthesis is provided to locate the axial position of the cross section with the largest radial deviation. In this method, the depth differences of any two sets of axisymmetric profiles are calculated, and then, the actual axis can be approximated by orthogonal synthesis of these two differences. The method is accurate and rapid and can easily solve the problem of the data deficiency caused by excessive bending of the twist drills.

The remainder of this article is organized as follows. Section II describes the designed structures of our measurement system. Section III illustrates the proposed segmentation method of the blade back and the reconstruction method of the axis for the twist drill. We detail our experimental results and analysis in Section IV. Finally, Section V concludes this article.

II. MECHANISM

A. Components and Principle

To improve the efficiency and accuracy of coaxiality measurement for twist drill, a novel mechanism based on 3-D measurement is designed, as shown in Fig. 3. Inspired by the applications of line structured light sensor in the literature [17], [23], [37], [38], [39], the mechanism is comprised of several main components such as programmable logic controller (PLC), differential encoder, line structured light sensor, and high-precision turntable. Among them, the turntable drives the drill to run around the axis of the turntable under the command of the PLC. Meanwhile, the differential encoder acquires a time-series angle signal and triggers the line structured light sensor to catch the point cloud data of the drill surface. The above trigger and rotation forms the core of the mechanism. On this basis, raw data are collected for blade back extraction and other following algorithms.

B. Data Acquisition

In the data acquisition phase, the twist drill is grasped and rotates around the axis of the turntable under the command of the PLC, and the differential encoder acquires time-series rotation signals from the turntable and triggers the sensor to catch the point cloud data of continuous contours of the twist drill. During the process, any i-th sample point data \( P_i = \{i, x_{ij}, z_{ij}\} \) rotated by \( \theta_i \) degree can be converted to a 3-D point data \( P'_{ij} = \{x'_{ij}, y'_{ij}, z'_{ij}\} \) from the sensor coordinate system to the measurement coordinate system, where \( i = 1, 2, \ldots, I \), \( j = 1, 2, \ldots, J \), with \( I \) the number of times the sensor was triggered and \( J \) the number of point clouds of a single sampling, as shown in Fig. 4. When the rotation reaches a cycle, the turntable is commanded to stop by PLC and the coaxiality calculation officially starts. The profile data of the twist drill collected by the line structured light sensor are shown in Fig. 5. To optimize visualization, the profile data are shown in 3-D coordinates and \( O_W X_W Y_W Z_W \) orientation views.

C. Coordinate Transformation

As shown in Fig. 6, in the measurement system, \( O_C X_C Y_C Z_C \) is the sensor coordinate system and \( O_W X_W Y_W Z_W \) is the measurement coordinate system. The conversion from the sensor coordinate system to the measurement coordinate system is

\[
\begin{align*}
\theta_i &= \frac{360^\circ}{I} \ast i \\
x'_{ij} &= x_{ij} \\
y'_{ij} &= (D - z_{ij}) \ast \sin \theta_i \\
z'_{ij} &= (D - z_{ij}) \ast \cos \theta_i
\end{align*}
\]

where \( i = 1, 2, \ldots, I \), with \( I \) the number of times the sensor was triggered, and \( j = 1, 2, \ldots, J \), with \( J \) the number of point clouds of a single frame contour. \( x_{ij} \) and \( z_{ij} \) are the profile data acquired by the line structured light sensor after the twist drill is rotated by \( \theta_i \) degree. \( x'_{ij}, y'_{ij}, \) and \( z'_{ij} \) are transformed data corresponding \( x_{ij}, z_{ij} \), and \( \theta_i \). \( D \) is the distance from the sensor to the axis of the turntable, which is a system parameter and needs to be calibrated. Based on the proposed rotational scanning mechanism, the 2-D profile data collected by the line structured light sensor can be converted into 3-D point cloud data of the twist drill using (1).

D. Calibration and Adjustment

Most detection systems based on line structured light sensors currently suffer from many calibration problems [23], [37], [39], [40], [41]. In this article, to determine the system parameter \( D \), a calibration block with a stepped shaft is designed to calibrate the system, as shown in Fig. 7. Since the surface of the twist drill is twined by spiral grooves, it may not be completely scanned according to the optical measurement constraints of the line structured light sensor based on triangulation. Therefore, the ladder on the calibration block can help the sensor installation so that the sensor can achieve a more perfect posture and position. The pose of the sensor can be described by Euler angles, including pitching, rolling, and yaw angle. In the measurement system, as shown in Fig. 6, they correspond to rotations about \( O_W X_W \)-, \( O_W Y_W \)-, and \( O_W Z_W \)-axes.
According to the adjustment and calibration rules from coarse to fine, a cyclic adjustment method based on three degrees of freedom is proposed. In detail, in the mechanism installation, the installation pose and position of the sensor are continuously being fine-tuned by adjusting installation height, rolling angle, and the position on $O_WY_W$-axis until it meets RULEs I–III.

**RULE I:** The calibration block appears completely in the field of the sensor view.

**RULE II:** The outline of the calibration block is close to a straight line and satisfies the following equation:

$$
\begin{align*}
&x_a - x_b = x_c - x_d \\
&y_a - y_b = y_c - y_d \\
&z_a - z_b = z_c - z_d \\
&\Delta z = |z_d - z_a| \\
&\Delta z \leq \Delta z_{th}
\end{align*}
$$
Fig. 3. Coaxiality measurement equipment for twist drill.

Fig. 4. (a) Illustration of point cloud collection. (b) Point cloud in sensor coordinate system. (c) Point cloud in measurement coordinate system. Pᵢ' corresponds to Pᵢ.

Fig. 5. Axial profile data of twist drill collected by the line structured light sensor. (a) Profiles data of the twist drill collected by the line structured light sensor. (b) OW YW direction view of the twist drill axial profile data by the line structured light sensor.

Fig. 6. Relationship between sensor coordinate and measurement coordinate. OC XC YC ZC is the sensor coordinate system and OW XW YW ZW is the measurement coordinate system.

Fig. 7. Calibration block diagram.

Fig. 8. Schematic of the calibration block contour. (a) Situation that meets RULE I but does not meet RULEs II and III. The dotted line in (b) is the situation where RULEs I and II are met, but RULE III is not met. The red line in (b) is the situation where RULEs I–III are all met. P_A, P_B, P_C, and P_D are evenly axial spaced points and P_B and P_C are the two endpoints of the ladder.

where as shown in Fig. 8(a), (x₀, z₀), (xᵢ, zᵢ), (xᵢ₋₁, zᵢ₋₁), and (xᵢ₊₁, zᵢ₊₁) are the coordinates of P_A, P_B, P_C, and P_D collected by the sensor, respectively. P_B and P_C are the two endpoints of the ladder. Δzₜₗₜ is the line threshold given by experience and is usually set to be less than three times z resolution.

RULE III: Fine-tune the sensor position on the OW YW-axis. As shown in Fig. 8(b), for points P_B and P_C on the calibration block, a series points data can be acquired and recorded as two sets, i.e., \{i, xᵢ, zᵢ\} and \{i, xᵢ₋₁, zᵢ₋₁\} for P_B and P_C, respectively. When the data satisfy the following equation:

\[
\begin{align*}
zᵢ + zᵢ₋₁ < zᵢ₋₁ + zᵢ₋₁, \\
zᵢ + zᵢ₋₁ < zᵢ₋₁ + zᵢ₊₁.
\end{align*}
\]

At this time, the position of the sensor on the OW YW-axis is the best, that is, the sensor is closest to the calibration block, and i is denoted as i*. Then, system parameter D can be obtained from the following equation:

\[
D = \frac{(zᵢ* + zᵢ*)}{2} + \frac{dₖ}{2}
\]
are the points, respectively, collected at the ath and bth times, and $S''$ and $P''$ are the transformed points calculated according to the following equation:

$$
\begin{align*}
    x''_{ij} &= x_{ij} \\
    y''_{ij} &= 2\pi \gamma^* i \\
    z''_{ij} &= z_{ij}
\end{align*}
$$

where $\gamma$ is the transformation coefficient, which is given manually. $i = 1, 2, \ldots, I$ and $j = 1, 2, \ldots, J$. $i$ is the number of times that the sensor was triggered. $J$ is the number of point clouds of a single sampling. $\{i, x_{ij}, z_{ij}\}$ is the ith sampled point dataset in the sensor coordinate system, and $\{x''_{ij}, y''_{ij}, z''_{ij}\}$ is the corresponding transformed dataset. Since there may be noises in the data acquisition process, a pass-through filter [42] is used to perform the basic outlier removal.

### B. Robust Target Region Segmentation

The goal of target region segmentation is to extract point cloud data located on circular cross sections. Currently, GMM [33] is widely used for object inspection or modeling segmentation models. In general, the standard GMM [43], [44] method assumes that the optical measure of each independent ground object follows the Gaussian distribution and uses the weighted average of the distribution of all ground objects to express the probability density function of the whole datasets. The expectation-maximization (EM) algorithm [44] is used to estimate the Gaussian distribution parameters for each independent feature. In summary, according to the above analysis, to apply the GMM-based segmentation model well, the target region must satisfy the following two rules.

**RULE IV:** The target point clouds must lie on a circular cross section.

**RULE V:** Each type of point cloud on the axial profile is independent and belongs to the same distribution.

1) **Analysis of Target Region Selection:** As shown in Fig. 11, the cross section of the twist drill is composed of three parts: the blade back, the blade lip, and the blade groove, which are marked with red, blue, and green, respectively. The profile formed by the blade back lies on a circle, which meets RULE IV. For the proposed triangulation-based measurement mode, it performs data collection by receiving light reflected from objects. It is subject to three constraints [18], [45]: 1) the measured point must be within the depth of field (DOF) of
the camera; 2) the measured point is within the field of view (FOV) of the camera; and 3) the angle between the reflected light of the measured point and its surface normal vector must be smaller than the incident angle. Therefore, during the scanning process, due to the shape characteristics of the twist drill and the limitation of optical constraints, only the blade back and part of blade lip can be scanned, as shown in Fig. 12 (the back of the blade is blue and the blade lip and few part of blade groove are red). Therefore, the point cloud data of the twist drill for one scan cycle are shown in Fig. 13(a). The 2-D data of the axial profile at the black line in Fig. 13(a) are shown in Fig. 13(b). The z-values of the point cloud show a ladder distribution, where the upper part is the blade back and the lower part is the blade lip. The statistical histogram of the z value of a certain region is shown in Fig. 13(c). The depth values z of the point cloud jointly constitute a GMM, which meets RULE V.

2) Homogeneous Region Model: We use GMM [33], [34], [36] to describe the depth value z of our point cloud data. In this model, the point clouds of the blade back are defined as the foreground, and the rest of the point clouds are the background. Therefore, the density function $p(z_i)$ of a point $z_i$ would be defined as

$$p(z_i) = \sum_{k=1}^{K} \omega_k f(z_i | \mu_k, \sigma_k)$$

(6)

where $i = 1, 2, \ldots, N$, with $N$ the number of point clouds, $k = 1, 2, \ldots, K$, with $K$ the number of the classes, $\omega_k$ represents the weight of data $z_i$ belonging to class $k$, and the constraints are given as follows:

$$0 \leq \omega_k \leq 1 \text{ and } \sum_{k=1}^{K} \omega_k = 1$$

(7)

where $f(z_i | \mu_k, \sigma_k)$ represents the Gaussian distribution, which is called the component of the mixture model, and is specifically expressed as

$$f(z_i | \mu_k, \sigma_k) = \frac{1}{\sqrt{2\pi}\sigma_k} \exp\left(-\frac{(z_i - \mu_k)^2}{2\sigma_k^2}\right)$$

(8)

where $\mu_k$ and $\sigma_k$ are the expected value and standard deviation of the $k$th Gaussian distribution.

Although the above method is simple and easy to implement, it has the following shortcomings: 1) the standard GMM method considers points to be independent of each other and does not consider the neighborhood effect of points, so the segmentation result is very sensitive to noise, and 2) this method expresses the depth characteristics of a single type of region as a single-peak Gaussian distribution, but it is not ideal for fitting and merging the depth of the point cloud data, especially the high-resolution data collected by the line structured light sensor (the homogeneous areas show significant multipeak distribution due to the line structured light sensor measurement differences introduced by the twist drill bending).

3) Segmentation Decision Model: In order to overcome the sensitivity of GMM to noise, we introduce local (neighborhood) spatial information such that the category of each point is not only related to its own depth but also affected by neighborhood points. On the basis of the homogeneous region model, according to the principle that the category of any point in the depth space is jointly determined by the probability that the point and its neighborhood points belong to the category, the segmentation decision model integrating spatial relations is established. A two-level division strategy is designed to perform local (neighborhood) spatial information extraction. The algorithm details are given as follows.

1) The point clouds are equally divided into $M^N \times T$ blocks along the three axes, namely, $O_C X_C$, $O_C Y_C$, and $O_C Z_C$, to obtain the blocks set $B$, $b_i \in B$, $i = 1, 2, \ldots, M^N \times T$. $M$, $N$, and $T$ are the number of blocks along the $O_C X_C$-, $O_C Y_C$-, and $O_C Z_C$-axes, respectively. $T$ is set to 1.

2) Each block $b_i$ is evenly divided into $n^m \times n^t$ patches along the three axes, namely, $O_C X_C$, $O_C Y_C$, and...
$O_C Z_C$, to obtain the patches set $F$, $f_j \in F$, $j = 1, 2, \ldots, m n t$. $m$, $n$, and $t$ are the number of patches along the $O_C X_C$, $O_C Y_C$, and $O_C Z_C$-axes, respectively. $t$ is set to 1.

3) The statistical histogram of the depth value $z$ in each patch $f_j$ is calculated, and the depth value $z$ with the highest frequency can be obtained according to the following equation:

$$zf_j = \arg \max_{z_i} \{h(z)\}, \quad k = 1, 2, \ldots, \tau \quad (9)$$

where $\tau$ represents the number of point clouds in patch $f_j$, $h(\cdot)$ represents the statistical histogram operation, $z''$ represents the depth value in each patch $f_j$, and $zf_j$ represents the most frequent depth value.

4) The initialization parameters of the improved GMM are given as follows:

$$\begin{align*}
\sigma_F &= \sigma_B = \left(\max\{zf_j\} - \min\{zf_j\}\right)/4 \\
\mu_F &= \sum_{j=1}^{m n t} zf_j - \sigma_F \\
\mu_B &= \sum_{j=1}^{m n t} zf_j + \sigma_B
\end{align*} \quad (10)$$

where $\mu_F$ and $\sigma_F$ and $\mu_B$ and $\sigma_B$ represent the expectation and standard deviation of the GMM corresponding to the foreground and background, respectively.

5) The GMM model is solved using the EM algorithm [44], which achieves the classification of each patch $f_j$.

Furthermore, considering the unavoidable noise, the segmented point cloud is filtered using the statistical filter statistical outlier removal (SOR) [46]. The segmentation results are detailed in Section IV.

C. Rapid Axis Reconstruction and Coaxiality Calculation

A rapid axis reconstruction method based on orthogonal synthesis is proposed. The method utilizes the extracted blade back data and the approximately reconstructed axis to prelocate the maximum deviation position of the axis. It is based on two characteristics of the coaxiality, that is, the coaxiality is proportional to the opposite phase differences and adjacent phase differences are independent of each other. The so-called opposite phase difference is the absolute difference between any two axisymmetric profiles, which is proportional to the coaxiality. The so-called neighboring phase difference refers to the difference between any two orthogonal axisymmetric profiles. Conversely, the coaxiality can be orthogonally synthesized by any two orthogonal axisymmetric profile differences.

1) Analysis of Axis Deviation: For parts with good roundness and coaxiality, when rotating around its axis, the absolute depth difference between the axial profile at any angle $\theta$ and its axisymmetric profile at $\theta + 180^\circ$ is approximately 0. When the coaxiality increases, the contrast difference increases. The two cases of in vivo and not-in vivo coaxiality are shown in Fig. 14. $R$ represents the radius of the twist drill, $C_e$ represents the coaxiality, $D$ represents the calibrated system parameter, and $C_{he}$ represents half of $C_e$. In Fig. 14(a), $z_1$ and $z_2$ represent the depth values of the same measuring points when the twist drill rotates at any angle $\theta$ and $\theta + 180^\circ$, respectively, satisfying the following:

$$z_1 \approx D - R - 0.5^\circ C_e \quad (11)$$
$$z_2 \approx D + (0.5^\circ C_e - R) \quad (12)$$

According to (11) and (12), we can obtain

$$C_e \approx z_2 - z_1. \quad (13)$$

Similarly, the situation in Fig. 14(b) satisfies the following equations:

$$z_1 \approx D - (R + 0.5^\circ C_e) \quad (14)$$
$$z_2 \approx D - (R - 0.5^\circ C_e). \quad (15)$$

We can also obtain (13) according to (14) and (15).

The above deviation proves that the axisymmetric difference can directly reflect the size of the coaxiality. The coaxiality can be orthogonally synthesized by two orthogonal axisymmetric profile differences. The graphical illustration is shown in Fig. 15. For any group of orthogonal directions $\overrightarrow{C_0 P_2}$, and $\overrightarrow{C_0 P_5}$, the axial deviation $\overrightarrow{C_0 P_1}$, can be generated by orthogonal synthesis, which can be obtained by the following equation:

$$|\overrightarrow{C_0 P_1}| = \sqrt{|\overrightarrow{C_0 P_2}|^2 + |\overrightarrow{C_0 P_5}|^2}. \quad (16)$$
2) Location and Calculation of Maximum Deviation for Axis: We use the orthogonal synthesis of any two sets of axisymmetric profile differences to reconstruct the actual axis. The specific algorithm is given as follows.

1) Two sets of orthogonal axisymmetric profiles are selected to contribute a point clouds set \( C_i = \{ x_{ik}, z_{ik} \} \), \( k = 1, 2, \ldots, K \), \( K \) represents the minimum number of point clouds for the two sets profiles. \( i = 1, 2, 3, 4 \), \( i \) corresponds \( \theta, \theta + 90^\circ, \theta + 180^\circ \), and \( \theta + 270^\circ \) angles.
2) The extracted point data are used to construct the quadratic spline function of the selected profiles.
3) The absolute differences of each two axisymmetric profiles are calculated, the absolute difference of each two axisymmetric profiles is reconstructed as \( z_{ik} = |z_{1k} - z_{3k}| \).
4) The approximate axis deviation profile is reconstructed by using (19) and expressed as \( SquABS = \{ x_{sk}, z_{sk} \} \)

\[
\begin{align*}
    x_{sk} &= x_{hk} = x_{mk} \\
    z_{sk} &= \sqrt{z_{hk}^2 + z_{mk}^2}.
\end{align*}
\]

5) The maximum deviation position of the actual axis is located by the following equation:

\[
    z_{s_{max}} = \max \{ z_{sk} \}, k = 1, 2, \ldots, K
\]

where \( z_{s_{max}} \) represents the depth value of the maximum deviation position of the estimated actual axis. To reduce the locating error, a threshold \( \Delta z \) is set, and the points whose \( z_{sk} \) value satisfies (21) are collected to form a position set \( XSM = \{ x_{sm}, z_{sm} \} \), where \( z_{sm} \) is the number of cross section positions.

\[
    z_{sk} \geq z_{s_{max}} - \Delta z.
\]

6) Equation (1) and the set \( XSM \) are used to obtain the cross section point cloud set \( CS \) from the segmented blade back data, where \( CS = \{ (x_{sm}, u), (y_{sm}, u), (z_{sm}, u) \} |\ t = 1, 2, \ldots, T \) and \( u = 1, 2, \ldots, U \}, \) with \( U \) the number of the point cloud data on each cross section. Then, we fit the center of each cross section in the set \( CS \) with the least-squares circle method to obtain the set of points \( AS \) for the actual axis, where \( AS = \{ (y_{ct}, z_{ct}) |\ t = 1, 2, \ldots, T \} \). Similarly, we use the same method to fit the axes of the benchmark to get the axes’ coordinate \( (y_{b}, z_{b}) \). Then, the coaxiality \( C_{r} \) is

\[
    C_{r} = 2^* \max_{t} \sqrt{(y_{ct} - y_{b})^2 + (z_{ct} - z_{b})^2}.
\]

According to the definition of coaxiality in the geometric tolerance standard [47], in the actual measurement experiment, the benchmark for coaxiality calculation is located at the axis of the twist drill shank.

### IV. EXPERIMENTS AND DISCUSSION

#### A. Setup

The experimental point clouds were collected by a line structured light sensor named MV-DP090-02B. For computational convenience, a region of interest is set for the sensor such that a single profile includes 1350 points. The specific parameters of the sensor are shown in Table I. The encoder is differential type, and the parameters of the turntable are shown in Table II. In addition, the point cloud framework PCL1.8.1 was used to process the collected point cloud data, based on a computer with windows 7, i7 CPU, and 8-GB memory.

#### B. System Calibration

In the experiment, the calibration block shown in Table III is machined to a precision of 2 \( \mu \)m. During the calibration process, through adjusting the Y connector and Y and Z fastener, the device is first fixed and adjusted so that the calibration block appears in the FOV of the line structured light sensor, as shown in Fig. 16. Second, through adjusting the Y fastener, the roll angle of the sensor is adjusted so that...
that the light plane of the sensor is parallel to the axis of the calibration block, and $\Delta z_{B_{B}}$ in (2) is set to $1 \mu$m. Then, by adjusting the Y connector, the position of the sensor in the $O_{W}Y_{W}$-axis direction is fine-tuned so that it is closest to the calibration block. Due to the machining error of the sensor bracket, the above three steps can be carried out in a loop to achieve the optimal calibration state, making it meet the three RULEs of calibration. By now, the optimal installation position is reached, $z_{B_{1}}$ and $z_{C_{1}}$ are measured, and parameter $D$ can be obtained. The point cloud data of one rotation of the calibration block are shown in Fig. 17. It can be seen that if the device is adjusted properly, the unfolded point cloud of the calibration block acts like a flat plane.

### C. Analysis of Blade Back Extraction

In the blade back extraction experiment, for our improved GMM-based model, $\omega_{F}$ and $\omega_{W}$ are both set to 0.5, and the transformation parameter $\gamma$ in (5) is set to be twice the diameter of the measured twist drill. Based on the fact that the maximum axis deviation is located at the work part of the twist drill, the region of interest for the line structured light sensor is set to be about 85 mm length, and each profile contains about 850 points. For each twist drill, the encoder continuously triggers the camera to collect about 1800 profiles in one revolution.

For the improved GMM-based blade back extraction model, the block and patch sizes of the two-level division strategy affect the segmentation effect. To analyze the specific effects of different block and patch parameters, extensive experiments have been carried out. Among them, the segmentation results of three block settings ($M$, $N$, and $T$) with the best patch settings ($m$, $n$, and $t$) are shown in Fig. 18. According to the number of triggers and the number of the point cloud data per profile, point cloud numbers of each block in the three settings are about 900, 61 200, and 15 300. From the theoretical and experimental analysis, it can be seen that the block and patch size of the two-level division strategy affects the segmentation effect. The block size affects the segmentation accuracy, while the patch size affects segmentation fine grainedness and copes with the misclassification introduced by the multipeak distribution of the homogeneous regions. The best segmentation performance is achieved when the block size is close to the sum of the single blade back and lip width, as shown in Fig. 18(c). The reason is that the distribution difference between the blade back and the blade lip is the most obvious, and the model is easier to converge when the block size is set like this.

Certainly, the settings of the block and patch affect the efficiency of segmentation calculation. When the number of blocks or patches is larger, the running time of the blade back segmentation is longer. For the best block setting $M = N = 10$ and $T = 1$, comparative experiments with different patch settings were carried out. The experimental results are shown in Table IV. It can be seen that the time consumption of whole blade back extraction grows with the number of patches. According to the experiments, for different block settings, when $m$ and $n$ reach 10 ($m \geq 10$ and $n \geq 10$), the segmentation can achieve satisfactory performance, that is, the size of the patch is less than one-tenth of the block size. The reason is that the twist drill is metal and there will be no large bends at small distances. When the block is properly set, this fine-grained patch size setting (one-tenth of the block size) can already reflect the bending of the twist drill and cope with the misclassification introduced by the multipeak distribution of the homogeneous regions. Therefore, considering that the parameters $M$ and $N$ contain actual physical meaning (the block size is close to the sum of the single blade back and the lip width), the block and patch parameters can be considered as configuration parameters of the algorithm in the actual measurement applications.
parameters can be set according to the specifications of the twist drill. In addition, although the parameter $N$ is related to the transformation parameter $\gamma$ in (1), as long as the parameter $M$ is appropriate, the block will contain regions such as the blade back and the blade lip. According to experiments, the block parameter setting of $N = M$ will achieve a satisfactory result.

Furthermore, to achieve more accurate segmentation, other algorithms have been attempted for comparative analysis, such as RG, conditional Euclidean (CE) distance, MB, and classical GMM [27]. For the transformed point cloud data, the RG algorithm assumes the area of the blade back as a plane, randomly selects the seeds, and uses a neighborhood normal vector threshold to terminate the growth of the regions with the similar normal vectors. The CE algorithm combines the intensity, normal vector, and the depth value of the point cloud to extract the region of the blade back. The MB algorithm utilizes the point cloud of the twist drill to generate a model and identify the region of the blade back. The comparison segmentation results of the blade back are shown in Fig. 19.

As can be seen from Fig. 19, the proposed method achieves the best segmentation results. Due to the rough and reflective surface of the twist drill, the MB algorithm has a large probability deviation in the spline estimation. Similarly, the RG algorithm shows poor performance in the segmentation of the blade back because the difference between the normal vectors is small due to optical constraints. The CE algorithm achieves the worst segmentation results.

D. Analysis of Maximum Deviation Location for Axis

To illustrate the measurement effect, the transformed point cloud data of four twist drills with different bending degrees are shown in Fig. 20. The point cloud after blade back extraction is shown in Fig. 21. From the extracted point cloud data of the blade back, the point cloud data of four profiles of $\theta$, $\theta + 90^\circ$, $\theta + 180^\circ$, and $\theta + 270^\circ$ are selected to estimate the maximum deviation location of the actual axis. According to the maximum axis deviation positioning method defined in Section III-C, the absolute differences $\text{ABSV}$ between $\theta$ and $\theta + 180^\circ$ and $\text{ABSH}$ between $\theta + 90^\circ$ and $\theta + 270^\circ$ were calculated, as shown in Fig. 22(a), (b), (d), (e), (g), (h), (j), and (k). Then, the actual axes of the twist drills are approximately constructed using orthogonal synthesis, as shown in Fig. 22(c), (f), (i), and (l). Hollow $\Delta$ is the estimated position of the maximum axis deviation. From Fig. 22(c) and (l), it can be seen that when the difference of two pairs of axisymmetric profiles is close, the deviation of the actual axis to the benchmark is much larger than that of both. When the two pairs of axisymmetric profiles differences differ greatly, the deviation of the actual axis to the benchmark is closer to the larger one, as shown in Fig. 22(f) and (i). This conforms to the rules of orthogonal synthesis.

According to the criterion of minimum containment area, the coaxiality of the twist drill is two times the radial distance from the center of the cross section at the maximum axial deviation position to the center of the benchmark. Here, the benchmark for coaxiality calculation is located at the axis of the twist drill shank. Since the turntable needs to clamp the twist drill shank to a certain length, the reference point of coaxiality is at least about 1 cm away from the clamping position and about 2 cm away from the end of the twist drill shank. In the practical applications of the proposed algorithm, the reference position can be set as an initialization parameter. Through the least-squares circle fitting method, the center of the benchmark and the cross section with the largest deviation were calculated, as shown in Fig. 23. In the experiment, the threshold $\Delta Z$ mentioned in (21) is set to 1 mm. The points of the located cross section with the maximum deviation are in blue, and its center is in red. The fitting center of the benchmark cross section is green.

Therefore, using the axial maximum deviation positioning method proposed in this article, only a few cross sections need to be center-fit, which greatly improves the calculation efficiency. According to experiments, the maximum deviation positioning and center fitting algorithms are generally completed within 90 ms. In addition, in terms of measurement efficiency, the maximum sampling frequency of the line structured sensor can reach 1000 Hz/s, as shown in Table I. According to the number of sampled profiles mentioned in Section IV-C, that is, the data acquisition of the twist drill can be completed within 2000 ms. Combined with the time consumed by the overall measurement algorithm, the coaxiality measurement of the twist drill can be completed within 3 s. The measurement efficiency of the proposed method is much higher than that of the CMM, which proves the application value of the proposed method in terms of efficiency.

Furthermore, a large number of experiments have been carried out on twist drills of various specifications. Among them, the ten measurement results of four drills with a length of 100 mm and a diameter of 10 mm corresponding to Fig. 20 are listed in Table V. The manual method of V-type bracket plus dial meter and the CMM method of ZEISS SPECTRUM were also used to compare the accuracy and stability of the measurements. The CMM is shown in Fig. 24. It can be seen that the proposed method achieves satisfactory measurement results in terms of accuracy and stability.

| Patch Parameter | Value | The Runtime (ms) |
|-----------------|-------|-----------------|
| $m$             | 8     | 159             |
| $n$             | 8     | 213             |
| $t$             | 1     | 271             |
| $m$             | 13    | 326             |
| $n$             | 21    |                 |
| $t$             | 1     |                 |
E. Effectiveness Analysis

To verify the effectiveness of the proposed coaxiality measurement method, calibration experiments are carried out. In the experiment, 80 twist drills with seven specifications and different bending degrees were measured. The specifications are shown in Table VI. To check the measurement deviation of
Fig. 22. Fitting curve of drills (No. 1–4) after rotating by \( \theta, \theta + 90^\circ, \theta + 180^\circ, \) and \( \theta + 270^\circ \) and the fitting curve of ABSV, ABSH, and SquABS. (a)–(c) Profiles of drill No. 1. (d)–(f) Profiles of drill No. 2. (g)–(i) Profiles of drill No. 3. (j)–(l) Profiles of drill No. 4. Hollow triangle \( \Delta \) is the estimated maximum axis deviation position.

Fig. 23. Least-squares circle fitting for cross section. The points of cross section with maximum deviation are blue. The center of the fitting circle is red, the center of the benchmark is green, and the fitting circle of the cross section is blue. (a) Drill No. 1. (b) Drill No. 2. (c) Drill No. 3. (d) Drill No. 4.

| Drill | Method | \( l_a \) (mm) | \( l_b \) (mm) | \( s_a \) (mm) | \( s_b \) (mm) | \( 4_a \) (mm) | \( 5_a \) (mm) | \( 6_a \) (mm) | \( 7_a \) (mm) | \( 8_a \) (mm) | \( 9_a \) (mm) | \( 10_a \) (mm) | Aver (mm) | Standard Deviation |
|-------|--------|----------------|----------------|--------------|--------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|-------------|--------------|
| 1     | Manual | 0.621          | 0.633          | 0.635        | 0.626        | 0.625         | 0.631         | 0.623         | 0.636         | 0.629         | 0.627         | 0.629         | 0.005       |
|       | This work | 0.790         | 0.450          | 0.675        | 0.536        | 0.680         | 0.710         | 0.540         | 0.750         | 0.690         | 0.540         | 0.605         | 0.017       |
| 2     | Manual | 0.620          | 0.623          | 0.624        | 0.622        | 0.627         | 0.635         | 0.629         | 0.635         | 0.623         | 0.627         | 0.630         | 0.005       |
|       | This work | 0.670         | 0.710          | 0.620        | 0.640        | 0.610         | 0.420         | 0.640         | 0.530         | 0.540         | 0.650         | 0.603         | 0.003       |
| 3     | Manual | 0.619          | 0.625          | 0.630        | 0.621        | 0.635         | 0.626         | 0.622         | 0.631         | 0.633         | 0.639         | 0.628         | 0.007       |
|       | This work | 0.546         | 0.543          | 0.544        | 0.543        | 0.547         | 0.545         | 0.543         | 0.544         | 0.546         | 0.544         | 0.545         | 0.001       |
| 4     | Manual | 0.770          | 0.550          | 0.560        | 0.690        | 0.550         | 0.540         | 0.430         | 0.570         | 0.530         | 0.520         | 0.571         | 0.094       |
|       | This work | 0.543         | 0.554          | 0.546        | 0.549        | 0.550         | 0.551         | 0.544         | 0.553         | 0.539         | 0.540         | 0.547         | 0.005       |
|       | CMM    | 0.465          | 0.462          | 0.467        | 0.469        | 0.468         | 0.470         | 0.466         | 0.472         | 0.469         | 0.468         | 0.468         | 0.003       |
|       | This work | 0.468         | 0.467          | 0.463        | 0.473        | 0.469         | 0.466         | 0.465         | 0.467         | 0.472         | 0.475         | 0.469         | 0.004       |

The proposed method from the ground truth, the high-precision CMM mentioned in Section IV-D was used to measure the co-axiality of the collected twist drills more precisely. For the CMM, the twist drills are sampled according to the following...
radial displacement does affect the measurement result, but the axial displacement does not [48]. However, considering that twist drills with a diameter of about 2 mm collected in the experiment are already uncommon smaller diameter drills, the proposed method already has broad application space. Therefore, in view of the influence of coaxiality on the radial runout of twist drills, according to the technical specifications for the radial runout of twist drills in the literature [49], it is proven that the proposed method has extensive application value. The detailed derivation is described in Section IV-F.

F. Analysis of Measurement Uncertainty

In the system, the measurement accuracy is mainly affected by the precision and resolution of the core components, such as turntable, differential encoder, and line structured light sensor. For the rotating-based measurement mode, the actual axis is obtained by measuring the radius $R$. Two kinds of displacements [48] may occur about the axis position including axial and radial displacement. Among them, radial deviation will bring errors, while axial deviation will not. Fundamentally, the radial error is mainly introduced by the eccentricity and running accuracy of the turntable. According to Table II, the eccentric of the turntable is less than 5 $\mu$m, so the uncertainty brought by the eccentric is 5 $\mu$m recorded as $\Delta c$ and $\Delta c \leq 5$ $\mu$m. The running angle error reacts worst when it occurs at the data acquiring moment, and the largest deviation occurs on the $O_w Z_w$-axis. The angle accuracy is 0.001°, as shown in Table II, so the uncertainty of running precision is $\Delta \eta = R^*(1 - \cos(0.001^\circ))$, $\Delta \eta \ll \Delta c$, which can be ignored. Furthermore, the repetition precision of the line structured light sensor is 3 $\mu$m as shown in Table I, so its uncertainty is denoted as $\Delta z$ and $\Delta z \leq 3$ $\mu$m. Considering the highest resolution of the line structured light sensor in the $z$-direction, the uncertainty $\Delta z$ of the line structured light sensor at the closest distance may reach 0.013 mm.

In the calibration stage, the maximum system error occurs when the axis of rotating shaft is in the light plane and produces the maximum eccentricity, and its uncertainty is denoted as $\Delta D = \Delta z + \Delta c$. In the measurement stage, the maximum system error occurs when the center of the drill cross section and the turntable axis are both in the light plane, and meanwhile, the maximum eccentricity of the turntable occurs. Then, the maximum deviation of the measured point is $\Delta z_p = \Delta z + \Delta c$. In short, the maximum deviation of the measured radius is $\Delta R = \Delta D + \Delta z_p + \Delta \eta$. Referring to the tolerance range of the radial jump variable of the twist drill [49], the maximum allowable coaxiality tolerance is $C_r = 0.03 + 0.01^* (L/D_d)$. $L$ and $D_d$ are the length and diameter of the measured drills, respectively. The proportion of the uncertainty of $R$ to the tolerance range of coaxiality is $\varepsilon$.

$$\varepsilon = \frac{\Delta R}{(0.03 + 0.01^*(L/D_d))}. \quad (23)$$

If the proportion $\varepsilon$ is desired to be controlled within 0.4, we can obtain the ratio of radius to length according to the highest resolution of the line structured light sensor in the
\[ z \text{-direction} \quad R/L \leq 1/10 \] (24)

where \( R \) is the radius of the twist drill. This is fully compatible with the coaxiality measurement requirements for most specifications of twist drills. It is confirmed that the proposed mechanism and method have certain industrial application value and can be applied to the coaxiality measurement of twist drills of various specifications.

V. CONCLUSION

Since twist drills are irregular rotating parts with complex surface, it is challenging to achieve coaxiality measurement accurately and efficiently. In this article, we propose an effective coaxiality measurement mechanism for twist drills. Four core components are contained in the mechanism, which can rapidly and accurately collect 3-D surface information of twist drills. Before formal measurement, a calibration process is performed to obtain system parameter \( D \) for compensating and eliminating system errors. In the data processing stage, an improved GMM model is developed to segment the acquired point cloud data according to discriminated features of different elements. To overcome the sensitivity of GMM to noise, local spatial information is introduced, which helps to extract the point cloud data of the blade back accurately and robustly. To improve the measurement efficiency, an axis reconstruction method based on orthogonal synthesis is designed. The novel method is accurate and can rapidly locate the maximum deviation of the actual axis from the benchmark. In addition, the corresponding instrument was developed and experiments were carried out. The experimental results show that the measurement method is effective with high efficiency (measuring time \(< 3\) s/pc), and the measurement error is within 0.020 mm. In addition, it is demonstrated that the proposed mechanism and method can be applied in many other practical industrial scenarios for online measurements, such as cylindricity measurement, roundness measurement, or runout measurement of rotating bodies. Furthermore, the measurement uncertainty is analyzed, and it is verified that the proposed mechanism is suitable for twist drills of various specifications.

In practice, several factors, such as the resolution of the line structured light sensor, the precision of the turntable, or the subdivision of the encoder, will affect the measurement precision of the coaxiality. It is better to choose a line structured light sensor with higher precision and thinner line laser to improve the precision of the collected data. Therefore, selecting core units with higher precision helps to improve measurement accuracy. In addition, the measurement results may be affected by tool wear or hardware platform jitter. Several schemes can be considered, such as replacing core components with higher resolution, adding seismic platform, and changing tools, to achieve the desired accuracy, precision, and reliability.
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