Journal of Mechanics Engineering and Automation 10 (2020) 27-36
doi: 10.17265/2159-5275/2020.01.004

Intelligent Automation Module-Based Gear Edge Grinding System

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Abstract: As industry progresses toward intelligent production and development, on-site workers that perform repetitive tasks will be replaced by intelligent machines. Currently, automation applications still have the following problems: (1) on-site personnel are required to line up the workpieces before a robot arm can pick it up; (2) the trajectory generated by offline programming software must be adjusted by on-site personnel in accordance with the processing results; and (3) because of workpiece positioning errors and tool wear, achieving acceptable processing results is difficult. This study developed intelligent application modules that solve the aforementioned automation application problems. These modules predict processing quality, generate trajectory, enable robot arms to load and unload randomly positioned workpieces, and automatically calibrate the system. An automatic gear edge grinding system was developed by integrating each module; the system increases the processing efficiency and solves the current problem of manual grinding being required after gear processing.

Key words: Intelligent automation module, grinding, calibration.

1. Introduction

As technology has progressed and evolved, industrial automation has become the objective of numerous corporations, with the advantages of reducing workforce sizes and improving product quality and safety. The usage of robot arms has increased progressively; according to estimation by the International Federation of Robotics, 3.152 million industrial robots will be used worldwide in 2020 [1]. Because they boost production and have capability for long working hours, high precision and repeatability, and low error rates, robot arms are crucial in industrial automation.

According to a report from the Gaogong Industry Research Institute, more than 35% of all industrial robots sold in 2017 were bought for use in load and unload, and this sector has been the most common application for industrial robots for numerous years [2]. Although the trajectory of robots used for palletizing can be directly designed through manual teaching, robot arms can also be programmed for automation applications other than the loading and unloading of products, for example, in advanced applications such as grinding, soldering, and spraying. In 2017, the market for grinding robots was approximately ¥24.2 billion in China; in 2020, it is expected to exceed ¥85 billion [2].

Compared with typical automation applications, advanced automation applications require more complex processing paths. Because developing advanced automation applications through manual teaching is difficult, the assistance of offline programing software is essential [3]. Despite numerous offline programming software programs existing in the current market, the following problems still occur when using robots for automated applications: (1) For a robot arm to pick up or process a workpiece, the workpiece must either be correctly lined up in the collection tray or the workpiece must have a positioning device; (2) The path produced by the offline programming software must be adjustable according to the actual processing quality; (3) Finally, due to workpiece positioning errors and tool wear,

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planned paths may require manual adjustment before they are used. To solve these three problems, this study developed intelligent application modules for integrating kinetic property analysis [4, 5], processing quality analysis [6], and automatic calibration technology [7]. The modules can predict the processing quality, generate paths [8], load and unload randomly placed workpieces [9], and automatically compensate for errors. By integrating the modules, a gear edge automatic grinding system was developed that automates the post-hobbing grinding and trimming processes, therefore reducing workforce requirements and increasing work efficiency and quality. During automation application planning using the system, the user is required only to input the workpiece model and select the work method; the system then automatically generates a motion path and displays the predicted processing quality results, with the user able to adjust the trajectory according to the predictions. After planning, the user can construct workstations according to the analysis results. After a workpiece has been randomly placed, the automatic calibration module guides the robot arm to pick up the workpiece, align its tool with the processing trajectory, and calibrate the process according to the tool's wear. After processing, the module automatically lines up the next workpiece.

2. Intelligent Application Modules

This chapter explains the intelligent application modules developed in this study.

(1) Optimal trajectory generation module: During advanced automation applications, CAD/CAM analysis is required to generate robot programs. However, the paths generated by the robot arm path generation software currently in use must be manually adjusted according to the processing quality. This study developed a system for quickly analyzing robot kinematics (e.g., singularities, joint limits, collisions, and grinding processing quality) and producing motion paths, thus assisting the user in rapid workstation distribution analysis and robot arm path generation.

(2) Automatic calibration module: During actual processing, the robot arm is easily influenced by positioning error and tool wear, which can destabilize the software-generated path. This study developed automatic calibration technology for automatically identifying a workpiece's position, automatically aligning the tool with the processing trajectory, and adjusting and compensating for the errors produced during tool mounting. Additionally, this study established random picking technology, which enables the random placing of workpieces; the module employs visual recognition and positioning to automatically pick up a workpiece and conduct error adjustment, ensuring trajectory accuracy and high processing quality.

After inputting a workpiece model into the path generator module for processing, the system automatically generates a motion path and displays the processing predictions. Users can then make adjustments according to these predictions to generate the optimal path. In accordance with the analysis results, the user can construct workstations and use the automatic calibration module to compensate for workpiece positioning and tool errors, thus enabling the robot arm to pick up randomly placed objects, line up the tool with the processing trajectory, make adjustments for tool wear, and line up the workpiece for the next work procedure. The module-based system is illustrated in Fig. 1.

2.1 Optimal Paths Are Generated Using Processing Quality Predictions

The optimal path generation module developed in this study is as follows: (1) robot arm kinematic analysis: This includes forward and inverse kinematic analysis of the robot arm, joint limitation analysis, singularity analysis, stiffness analysis, and path generation for continuous motion. After selecting the processing type and position distribution, a processing

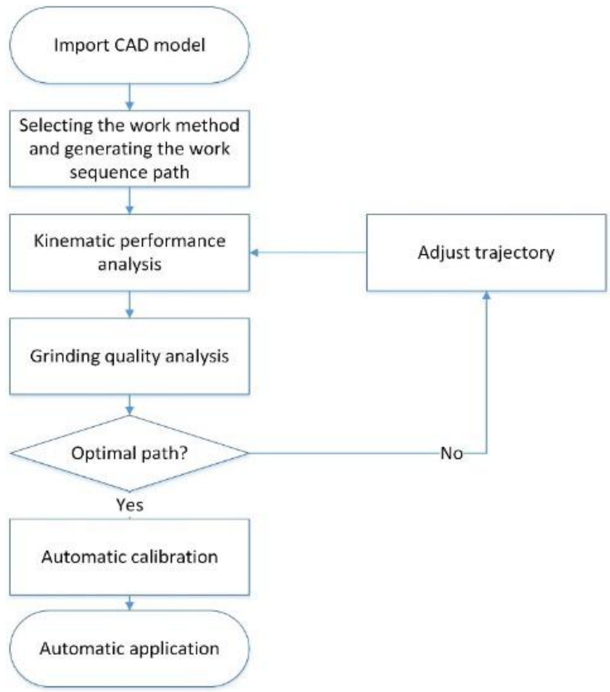

Fig. 1 Intelligent modules and system.

trajectory is automatically generated; (2) collision detection: After a continuous motion processing trajectory for the robot arm is generated, analysis is required to determine whether a collision may occur between the robot arm, workpiece, tools, and surrounding hardware equipment or whether the objects are too close to each other. The module automatically adjusts the path to ensure functional processing; (3) prediction of grinding processing quality: After generating a processing trajectory that has acceptable dexterity but does not have singularities or collisions, the processing quality is analyzed. By predicting grinding quality using the processing tool and the amount of workpiece interference, the user can predict whether the planned grinding is insufficient and adjust the path according to the analysis results.

Six-axis articulated robot arms satisfy two conditions namely that the three upper axes intersect and the second and third axes are parallel. According to inverse kinematics analysis, three quadratic polynomials can be used to calculate the inverse kinematic solution sets of the arm's eight postures. Additionally, by selecting different inverse kinematic solution sets, a path can be planned that avoids singularities, axial displacement constraints, and obstacles. However, if the incorrect inverse kinematic solution set is selected during path planning, the robot will exhibit a rapid speed change or make an unpredicted motion.

Fig. 2a illustrates the two sets of inverse kinematic solutions for a 2-DOF robot. $^{A}\theta_{ij}$ and $^{B}\theta_{ij}$ represent the j^{th} set of inverse kinematic solutions at points A and B, respectively. If the robot is commanded to move from A = ($^{A}\theta_{11}$, $^{A}\theta_{21}$) to B, the inverse kinematic solution sets of the two solution branches would be ($^{B}\theta_{11}$, $^{B}\theta_{22}$) and ($^{B}\theta_{11}$, $^{B}\theta_{22}$). However, if the robot is commanded to move from ($^{A}\theta_{11}$, $^{A}\theta_{21}$) to ($^{B}\theta_{11}$, $^{B}\theta_{22}$), the robot must move further and pass through at least one singularity of the two at $\theta_2 = 0°$ and $180°$. By conducting path planning using inverse kinematic solution sets from the same branch, energy can typically be saved and singularities, joint limit constraints, and collisions avoided.

The inverse kinematic solution with the largest singular-free joint space should be selected when conducting path planning to reduce the number of times the inverse kinematic solution must be changed. Fig. 3a shows the joint spaces for the first three joints of a 6-DOF robot. The four regions indicate the intervals between the positive and negative solutions of the two discriminants before conducting inverse kinematic analysis. Fig. 3b shows the three upper joint spaces, which is separated into two ranges by the singularity curve ($\sin\theta_5 = 0$). Fig. 4 displays the branches of the eight inverse kinematic solutions for a 6-DOF robot, with each "+" sign representing a positive solution in the quadratic polynomial of the discriminant ($\pm\sqrt{b_i^2 - 4a_i c_i}$). To calculate the approximate value of the joint space for the (+, +, +) branch, the interval area of (+, +) from Fig. 3a should be added to the interval area of (+) in Fig. 3b. During

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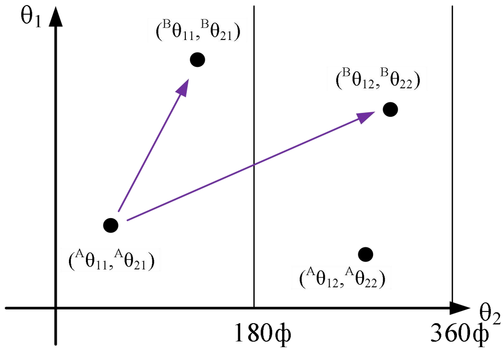
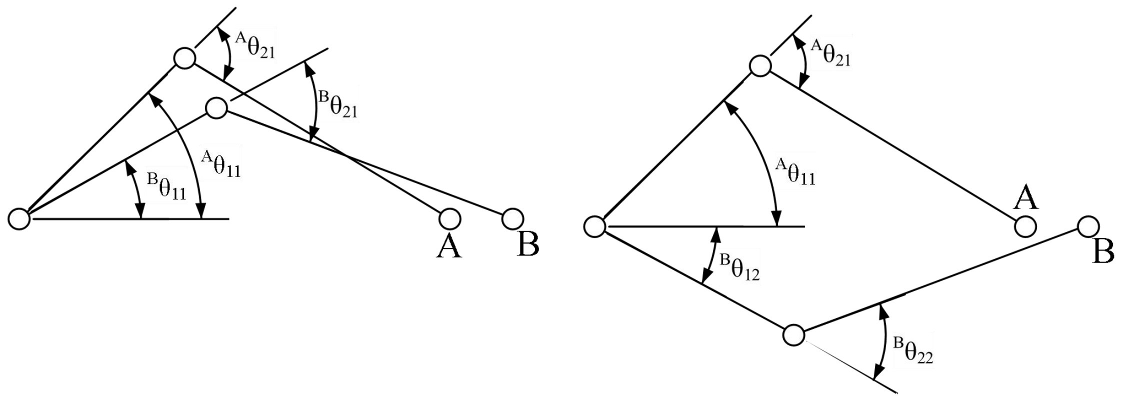
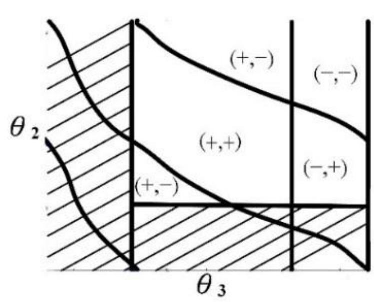


(a) Axial displacement range

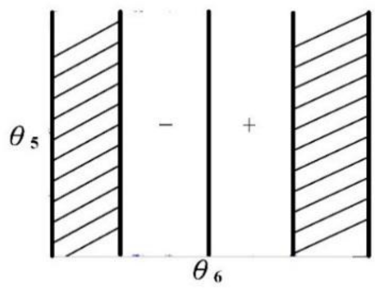


(b) Workspace

Fig. 2 Two inverse kinematic solution sets for two-DOF robots.



(a)



(b)

Fig. 3 Axial displacement range.

path planning, the inverse kinematic branch with the largest joint space is employed to reduce the number of times the inverse kinematic solution must be changed. If path planning requires selection of a different set of branch solution, the inverse kinematic solution set with discriminant value closest to 0 is selected. When the discriminant value is close to 0, the inverse kinematic solutions of different sets are close.

For the joint limits, displacement θ_i is within its joint limits if $(\theta_{i\max} - \theta_i)(\theta_{i\min} - \theta_i) < 0$, where $\theta_{i\max}$ and $\theta_{i\min}$ represent the maximum and minimum joint limit of i^{th} axis, respectively. The closeness to joint limits is evaluated by:

$$\eta_i = \frac{(\theta_{i\max} - \theta_i)(\theta_{i\min} - \theta_i)}{(\theta_{i\max} - \theta_{i\text{ave}})(\theta_{i\min} - \theta_{i\text{ave}})} \tag{1}$$

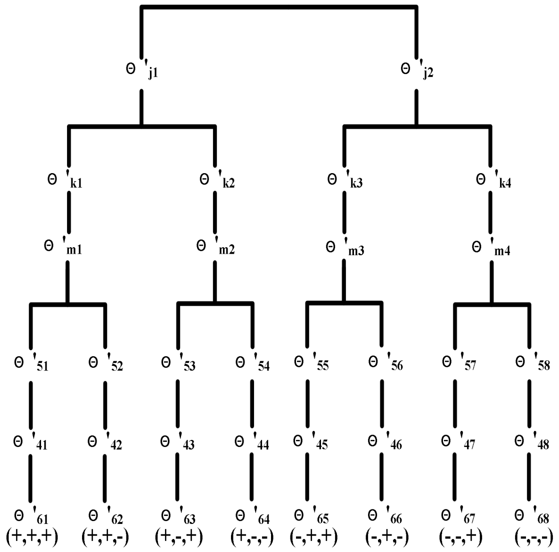


Fig. 4 Inverse kinematic solutions of a 6-DOF robot.

where $\theta_{i\mathrm{ave}} = \frac{\theta_{i\mathrm{max}}+\theta_{i\mathrm{min}}}{2}$. Measure $\eta_i = 1$, $\eta_i = 0$, and $\eta_i < 0$ indicate θ_i is in the middle of $\theta_{i\mathrm{max}}$ and $\theta_{i\mathrm{min}}$, reaches its joint limits and exceeds its joint limits, respectively.

The singularity, stiffness, and dexterity of the robot arm can be represented using Plücker coordinates. Because the three upper axes of the robot arm intersect, the 6 × 6 Jacobian matrix can be simplified into four 3 × 3 affiliated matrices in Eq. (2) to quickly analyze the kinematic properties of the robot arm. For example, robot arm rigidity can be analyzed using the maximum and minimum singularity value of the $C^{\mathrm{T}}C$ compliance matrix in Eq. (3). In Eq. (3), k_i is the rigidity coefficient of the i^{th} axis. The proximity to the singularity can be determined using the determinant of the Jacobian matrix in Eq. (4). The dexterity of the robot arm is analyzed using the ratio between the maximum and minimum singularity values of the Jacobian matrix $\mathbf{JJ}^{\boldsymbol{T}}$, ensuring the kinematic performance of the robot arm.

$$\begin{bmatrix}\boldsymbol{\omega}_6\\ \mathbf{v}_\mathrm{p}\end{bmatrix} = \mathbf{J}\dot{\boldsymbol{\theta}} = \begin{bmatrix}\hat{\mathbf{e}}_1 & \hat{\mathbf{e}}_2 & \hat{\mathbf{e}}_3 & \hat{\mathbf{e}}_4 & \hat{\mathbf{e}}_5 & \hat{\mathbf{e}}_6\\ \mathbf{r}_1\times\hat{\mathbf{e}}_1 & \mathbf{r}_2\times\hat{\mathbf{e}}_2 & \mathbf{r}_3\times\hat{\mathbf{e}}_3 & \mathbf{r}_4\times\hat{\mathbf{e}}_4 & \mathbf{r}_5\times\hat{\mathbf{e}}_5 & \mathbf{r}_6\times\hat{\mathbf{e}}_6\end{bmatrix}\dot{\boldsymbol{\theta}} = \begin{bmatrix}\mathbf{J}_1 & \mathbf{J}_3\\ \mathbf{J}_2 & \mathbf{0}\end{bmatrix}\dot{\mathbf{q}} \tag{2}$$

$$C = (\mathrm{J}K^{-1}\mathrm{J}^T)^{-1} \tag{3}$$

$$\begin{aligned}\mathrm{Det}[\mathbf{J}] =& -\{a_3\sin\theta_3 - \cos\theta_3\sin\alpha_3 d_4\}[(-d_4\sin\alpha_1\sin\alpha_3\sin\theta_3 - a_3\sin\alpha_1\cos\theta_3 - a_2\sin\alpha_1)(\cos\theta_2)\\ &- (d_4\sin\alpha_1\sin\alpha_3\cos\theta_3 - a_3\sin\alpha_1\sin\theta_3)(\sin\theta_2) - a_1\sin\alpha_1]\langle\sin\theta_5\sin\alpha_4\sin\alpha_5\rangle\end{aligned} \tag{4}$$

For the collision detection, the voxel-based method is employed to conduct collision analysis. This method divides the models into finite elements and analyzes the relationship between each element to determine any interference. If interference between two elements is detected, a collision would occur. In this case, the workpiece and tool must be reconfigured to generate a new trajectory. The analysis accuracy of the voxel-based method is related to the size of the elements; employing smaller elements enables more accurate analysis results but requires more computation time. The linear distance between the centers of two spherical elements can be used to conduct element collision analysis. If this linear distance is smaller than the sum of the radii of the elements, interference will occur between the two elements in Fig. 5:

$$\|\boldsymbol{O_a} - \boldsymbol{O_b}\| \le (\mathrm{R_a} + \mathrm{R_b}) \tag{2}$$

The voxel-based method and workpiece element interference conditions are used to analyze workpiece-tool contact during processing. The amount of contact is crucial for analyzing the grinding processing conditions. The amount of grinding that will occur on a given path is calculated and displayed on the operational interface. The user can then make adjustments in areas with insufficient or excessive grinding.

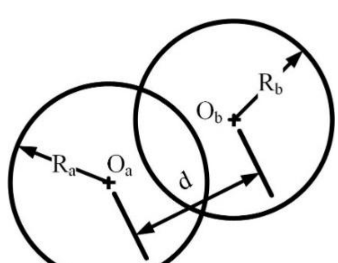


Fig. 5 Detecting potential collisions using the voxel-based method.

2.2 Automatic Calibration Technology

Currently, automation using a robot arm requires an operator to line up workpieces at the tray or a positioning device; only then can the robot arm perform follow-up motions. During automation applications, the path generated using programming software may be unusable or processing quality may be unstable because of workpiece scale tolerance, relative errors between items, and tool wear. The automatic calibration module developed in this study includes the following technology: automatic workpiece position recognition, automatic processing trajectory alignment, and tool center point (TCP) calibration. Additionally, this study developed technology incorporating machine vision and positioning, enabling the robot arm to automatically pick up workpieces with random positions and the system to conduct calibration for ensuring trajectory preciseness and processing quality.

The technology for automatic workpiece position recognition, pickup and automatic trajectory calibration: (1) establishes the position and orientation relationships between the coordinates of the image sensor mounted on the loading platform, the physical workpiece, and the workpiece's two-dimensional image on the sensor; (2) establishes a method for calibrating the internal and external variables of the image sensor; (3) enables the use of workpiece contour alignment technology. After a deploying physical workstation, the user can employ the workpiece calibration technology to analyze the positioning error of the workpiece. Subsequently, the user can adjust the workpiece position or trajectory for reducing this error. A description of related technology follows.

Automatically picking of randomly positioned workpieces [9]: An image sensor is set above the loading platform, and the coordinates of the robot arm relative to the image sensor are calibrated. Visual recognition is employed to determine the workpiece's position. The workpiece coordinates are converted into the coordinates of the robot arm. Finally, the robot arm is controlled to pick up the workpiece.

Identifying the actual processing trajectory and performing calibration in accordance with the default processing trajectory [10]: When the robot arm picks up a randomly positioned workpiece from the loading platform, the processing trajectory should be aligned twice to ensure correct grinding of the gear edge. The proposed method uses the image sensor to capture the grinding trajectory under default conditions. Automatic calibration technology is then employed to align the workpiece with the grinding trajectory and to adjust the grinding trajectory errors determined from both alignment processes. After the error between the processing position and actual position has been analyzed, processing trajectory correction methods are used to adjust the processing position for ensuring processing quality. In gear grinding applications, a gear is picked up by the robot arm and moved to the image sensor position for image capture. Analyzing the position of the gear edge yields the offset between the actual and predicted grinding trajectories.

The TCP automatic calibration system is employed by two image sensors (Fig. 6). The A- and B-axes are defined as the center axes of the field of view for image sensors 1 and 2, respectively. The C-axis is defined as the direction perpendicular to both the A- and B-axes. Planes 1 and 2 are the planes perpendicular to the A- and B-axes, respectively. The TCP obtained by image sensors 1 and 2 is located on planes 1 and 2, respectively [7].

The TCP calibration process has four steps: (1) establishment of the calibration system, which consists of numerous image sensors and axes that intersect; (2) determination of the conversion relationship between the robot arm reference coordinate system and image sensor reference coordination system; the image-sensor-coordinate motion vectors are converted into robot-arm-coordinate motion vectors; (3) use of the visual server to control the robot and obtain the calibration reference point; this point must have the

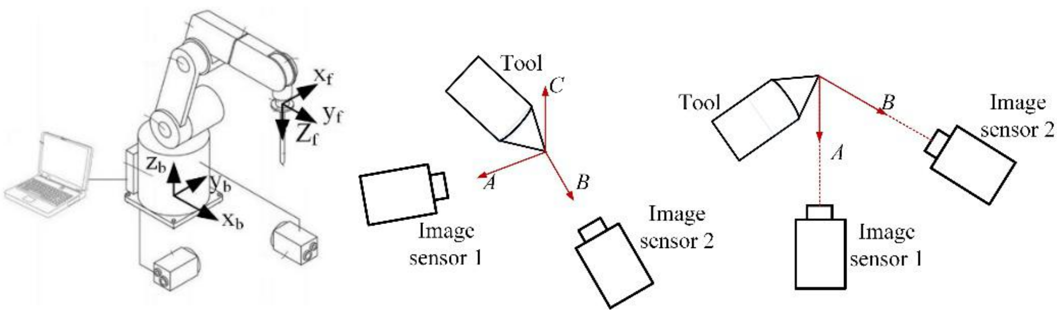


Fig. 6 TCP calibration system.

same position as the TCP but a different orientation; and (4) calculation of the actual TCP position.

3. Gear Edge Grinding Application System

The common features of manufacturing factories include sultriness, noisiness, and repetitive operations, which are factors that are unpleasant for workers and thus lead to the labor gap. The environment in processing factories often causes workers to feel bored and lose concentration, causing psychological fatigue that leads to adverse symptoms (e.g., physiological exhaustion). Not only does this endanger worker safety, it also results in inconsistent product quality. Numerous factories now employ automation to address this concern. Introducing industrial robots into the parts of the production process that are dangerous or require repeated performance of a particular task enables more efficient utilization of human resources.

This chapter explains the integration of the intelligent automation modules and the development of the gear edge automatic grinding system. Robot arms can be used for the following automation applications: loading and unloading of workpieces, deburring and chamfering. Factories can employ the intelligent application modules to achieve the following:

(1) Intelligent pickup and placement of workpieces: After placing a workpiece in the loading area, the feedback coordinates obtained through machine vision recognition are transmitted to the robot, enabling it to pick up the workpiece. After processing has been completed, the actual condition of the unload area is determined and transmitted to the robot, enabling the robot to place the processed workpiece at a usable grid position.

(2) Pickup function featuring decentering calibration: Before image capture, the fixed position of the worm wheel is obtained by the angle of rotation of each gear in the workpiece. After recording the start of the trajectory and the center deviation distance of each gear, sine functions are employed to perform curve fitting and calculate the possible deviations, and the deviations are compensated to adjust the tool coordinates and perform verification. The process is repeated until the deviations are within a predetermined error range.

(3) Automatic alignment of the processing trajectory: According to the set angle rotation of the workpiece, machine vision is employed to label the displacement of the teeth grinding starting point near the center of the image. The deviation between the current teeth grinding starting point and center of the image is calculated. The deviation is added to the tool position of the rotating workpiece, thus aligning the gear grinding starting point with the center of the image.

(4) Gear edge grinding: The workpiece alignment value is substituted into the work coordinates configured in each grinding process setting. Grinding then proceeds.

The automatic gear edge grinding system developed in this study employs the ITRI 12A62 robot arm (Fig. 7).

The work process of the automatic tool edge grinding system developed in this study consists of the following four stages. (1) Initialization: The system

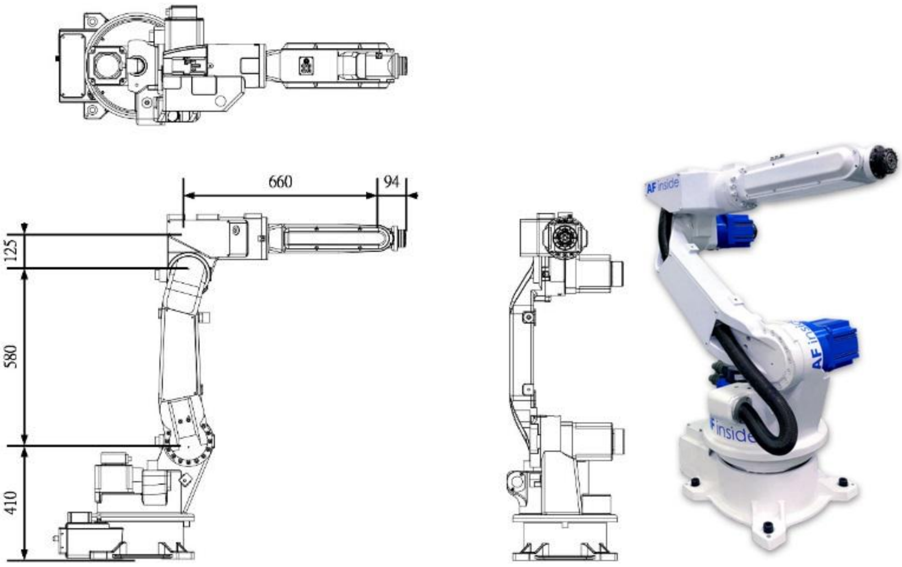


Fig. 7 12A62 robot arm.

can be used on gears of different sizes. Before grinding processing, automatic machine vision recognition or notification by the user of the appropriate gear code is required to determine the processing parameters, such as the processing trajectory generated by offline software and gear geometry variables. (2) Automatic self-measurement and calibration: During the first operation of the system and after the system has operated for a certain amount of time, automatic self-measurement and calibration are required to ensure standard operation of the system; these processes include using a calibration block to evaluate the accuracy of the image sensor above the loading platform, calibrating the relationship between the mounted image sensor and robot arm, and conducting decentering measurements of the robot arm gears. The proposed detection method uses the image sensor to identify the size and position of the first gear's teeth. The gear is then rotated in place, and its position and size deviation are recorded to estimate the deviation condition (Fig. 8). (3) Gear grinding processing: After the evaluation has been completed, gear edge grinding can be performed. The grinding process involves the pickup of a randomly positioned workpiece, alignment of the processing trajectory, grinding, and alignment of the processed gear.

The proposed system implements automated production into the gear grinding process, which was originally conducted only manually. By enabling

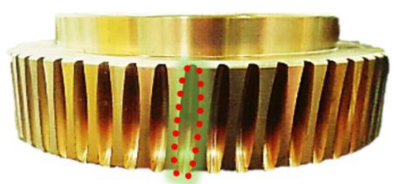
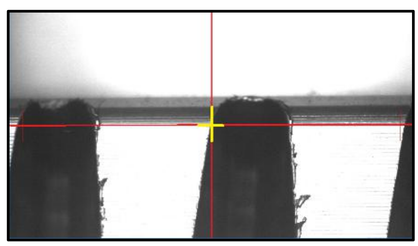
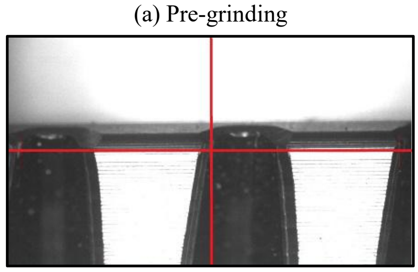


Fig. 8 Gear tooth size and position determination.



(a) Pre-grinding



(b) Post-grinding

Fig. 9 Results of automated grinding of a gear edge.

loading and unloading of randomly positioned workpieces and performing automatic trajectory calibration, this system saves the cost of a loading plate and positioning device. The results obtained using the automatic grinding system are displayed in Fig. 9. The system achieved grinding of similar quality to manual grinding while increasing the processing efficiency by 20%. Furthermore, processing quality can be maintained using this system even after operation for a long period.

4. Conclusion

This study developed intelligent application modules and integrated the modules into an automatic gear grinding system, which has the following three features: (1) capable of generating the optimal path by predicting processing quality; (2) automatic calibration technology for tools and workpieces; and (3) an automatic gear edge grinding application workstation. The module scales of the automatic gear edge grinding application workstation are as follows: (1) The automatic path generation technology produces a processing trajectory without singularities and collisions and with smaller joint angle changes than the user set value; (2) The success rate of the pickup and processing trajectory functions exceeded 99%, and actions could be completed in less than 40 s; (3) The automatic TCP calibration technology completed calibration within 1 min, with errors less than 0.1 mm; (4) The errors in the gear edge grinding width were within ±0.3 mm, similar processing quality to manual processing and increasing the work efficiency by 20%. Aside from producing a human-machine interface for related functions, this study strengthened the automation application, improving the automation application modules and the technological competitiveness of Taiwan while reducing the time required for process planning.

At present, automated application modules are used in Taiwan mainly in factories of Japanese firms, such as FANUC, Mujin, and Keyence, which account for 80% of the Taiwanese market share and thus control the price, delivery date, and profits of Taiwanese intelligent applications. Because the technology of advanced intelligent automation applications is a difficult field of research and development, Taiwan has yet to release an advanced intelligent application module. By implementing a domestically developed intelligent module, this study aims to increase the acceptance among Taiwanese firms of domestically produced controllers as well as increase the reliance on these controllers and the confidence in their properties. When purchasing automation application modules and robot arms, terminal users will hopefully be encouraged to purchase Taiwan-developed controllers with a higher price-performance ratio rather than controllers from Japanese and European brands.

Acknowledgement

The researchers would like to express gratitude toward the Technology Development Program of the Ministry of Economic Affairs and the Industrial Technology Research Institution for providing funding and support.

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