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Learning optimal measurement and control of assembly robot for large-scale heavy-weight parts

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Abstract— Due to their advantages of high speed, high accuracy, high flexibility, and low cost, assembly robots are widely used in electronics and automotive industries. However, it is still a significant challenge for large-scale, heavy-weight part assembly using industrial robots. First, the deformation and motion errors of industrial robots caused by big payload cannot meet the accuracy requirement of large structure assembly. To solve this problem, an online kinematics compensation method based on Gaussian Process Regression is developed to predict and compensate the deformation and uncertainties of a large structure assembly robot. Second, before the assembly process, the optimal assembly path has to be planned. To this end, we propose an assembly path planning method based on learning from demonstration. Finally, an event-based control method is deployed to achieve optimal assembly cycle time to improve assembly efficiency and performance. An experimental system is developed to validate the proposed algorithm for large structure assembly and the results demonstrate that the proposed method can improve the assembly efficiency by more than 40%.

I. INTRODUCTION

A. Problem statement

In ship-building, aerospace, aviation, hydro-power plant, etc. The final assembly of large-scale, heavy-weight parts depends on many fixtures and jigs, which is lack of adaptability to structure changes and dimension variations. Hence, the existing manufacturing method is no longer able to satisfy the flexible, multi-variety, and, small-batch manufacturing requirement. Once, the assembly part changes, the configuration of fixtures and jigs has to be re-designed accordingly.

At present, robotic assembly is widely used in electronics, automotive industries, etc due to its high speed, high accuracy, high flexibility, and low cost; however, the automated robot assembly of large-scale heavy-weight part still faces the following challenges:

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First, the deformation and uncertainty of robot caused by heavy-weight payload cannot be neglected and is difficult to compensate by using a general parametric calibration model due to the variant weight and placement position of assembled part. On the other hand, to reduce the deformation by stiffness improvement would lead to a bulky robot structure. Inspired by the fact that human arm has no accurate kinematics model but still can perform precision assembly, in this paper we propose an online kinematics compensation method based on Gaussian Process Regression (GPR), which could estimate and compensate the deformation caused by unknown weight and placement position, leading to improved absolute positioning accuracy.

Second, the axis of fixed hole is required to be precisely measured and the assembly path of moving peg also has to be planned before assembly, also be monitored and compensated during assembly. Since no force senor could satisfy the measurement requirements of wide-range and high-resolution simultaneously for heavy-weight payload, sensor-based contact measurement fails. To this end, an optimal assembly path planning method based on learning from demonstration (LfD) is proposed. A small-size lightwight demonstration part is assembled under the monitor of stereo vision and the optimal assembly path is learned. Then, the robot follows the planned assemble path to realize large-scale part assembly under the monitor of stereo vision.

Third, the assembly process is required to guarantee "do it right the first time" to avoid jamming, taking into account large-scale heavy-weight part. For small parts assembly, the assembly process could be iteratively conducted by identifying the contact force change and repeat the assembly task until the optimal assembly process is figured out; however, it is difficult to be used for heavy-weight part since the force sensor fails to detect the relatively small contact force between mating parts during assembly. To this end, an event-based assembly process control is proposed to improve assembly performance and efficiency.

B. Related work

To realize precise assembly, position control and force control are usually intergraded. Generally speaking, the position control is first used to align the mating parts and force control is applied after contact between mating parts to limit the contact force to avoid damage to both assembly parts and robot. However, the force control strategy based on the small contact force between mating parts would fail due to the heavy-weight payload since no sensor could satisfy wide-range and high-resolution measurement simultaneously. To be specific, the sensor measurement range has to support the heavy-weight part while the minimal contact force the sensor can detect could damage the mating part. So, the position and orientation control is preferred to avoid jamming for large-scale and heavy-weight part assembly. In this case, the robot is expected to hold the capabilities of high absolute positioning accuracy and optimal assembly path planning.

An approximate Jacobian controller is proposed where the exact kinematics and Jacobian matrix are not required [1]. However, only set-point control of the robot is achieved. Later, an adaptive Jacobian controller is investigated to track a given trajectory without the exact kinematics and Jacobian matrix; however, non-parametric uncertainties such as friction and disturbance would cause a risk of instability [2]. To mitigate this problem, a control scheme is proposed in [3] to deal with uncertainties in actuator dynamics, robot dynamics and kinematics. However, this method is likely to cause malfunctions through the singular point, thereby limiting the practical applications. Recently, an artificial neural network based adaptive controller is also proposed, where three-layer neural networks are used to compensate uncertainties in the manipulator kinematics and dynamics [4]; however, it is difficult to execute online.

To solve this problem, we propose a GPR-based kinematics compensation method, which is capable of predicting and compensating the deformation online. For this model-based learning method, the robot joint angle and the pose (including position and orientation) of assembled part in sensor coordinate frame is learned and updated, without any pre-knowledge of weight and placement position. As a result, the high absolute positioning accuracy is achieved to satisfy the requirement of heavy-weight part assembly.

Learning from Demonstration (LfD) is a strategy which enables the robot to perform same activity by learning the skills of human being, which can be tracked to 30 years ago, when it is also called programming by demonstration. There are two different kinds of demonstrations for robot training data: tele-operation method, which reflects the position and force from the robot via joysticks, has been used for assembly tasks [5], [6]. On the other hand, the shadowing method is much more promising since the operator performs tasks by using his own hand and perception and then robot mimic the human operator movement[7], [8].

It is difficult to directly obtain the optimal assembly path for large-scale heavy-weight part by using teach pendent of robot. To this end, the optimal assembly path is generated in the way that a small-size, light-weight demonstration peg is inserted into the fixed hole by the human manual demonstration, which is recorded by a stereo vision sensor. Then, the optimal path is learned and deployed in the robot control and the assembly process would follow the optimal path.

The event-based control method was first proposed by Xi [9]. For this technique, another non-time motion reference instead of conventional time reference is introduced. The critical step of event-based control is to choose an appropriate non-time reference. The event-based control has been used for the planner and controller in terms of events to improve control stability. For example, the event-based control is used to track path for a passive dance robot to overcome the lack of acceleration capability [10]. It is also deployed for automated manufacturing systems [11], tele-operation system with communication delay [12] and so on.

In this paper, the event-based control is used to achieve optimal assembly cycle time taking into account the different fit tolerances at different position, resulting in improved assembly performance and efficiency.

In short, the main contributions of this paper are as follows:

(1) proposes a GPR-based kinematics compensation method to improve the robot moving accuracy;

(2) proposes a LfD-based assembly path planning method to obtain optimal assembly path;

(3) proposes an event-based control method to shorten assembly cycle time.

II. WORKING PRINCIPLE

For large-scale, heavy-weight part assembly, one of the mating parts with hole is fixed and another one with peg is moved by a robot. The proposed assembly system mainly consists of a 6 DOF (degree of freedom) robot, a real-time stereo vision sensor. The moving peg is mounted on the robot end-effector. The real-time stereo vision sensor is used to track the circle markers mounted on both the small-size demonstration peg and large-scale assembled peg. It is noted
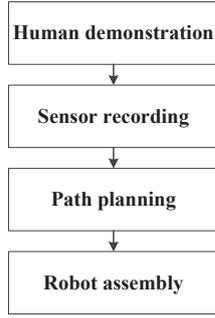
Fig. 1.   General framework of the large-scale heavy-weight part assembly

that the marker location with respect to demonstration and assembled pegs could be precisely determined in advance. The diameters of demonstration and assembled peg are expected to have the same fit tolerance.

The flowchart of large-scale, heavy-weight part assembly based on demonstration learning can be described as follows: human demonstration, sensor recording, path planning and robot assembly as shown in Figure 1. For this technique, operator assembles a small-size light-weight demonstration peg, which can be easy to be held by human being. Then, the movement trajectory of markers on the demonstration peg is recorded by the sensor and then the optimal assembly path of assembled peg is planned. Last, the robot moves the large-scale, heavy-weight assembled peg following this planned path. Only the demonstration peg assembly task is performed by human operator and then human assembly skills are learned by the robot such that the other tasks are automatically executed by the robot.

III. KINEMATICS MODEL WITH DEFORMATION

Due to the inevitable and variant deformation of robot for heavy-weight part assembly, it is difficult to set up the explicit kinematics model. To solve this problem, the robot implicit motion model is learned by a GPR model, which learns the relationship between input and output of the system based on a set of training data. So we can predict the corresponding pose of assembled part for a set of given robot joint input. It has good adaptability for high-dimension, small-sample and nonlinear problems.

A. GPR model

First, while controlling control each robot joint to move to a set of angles, the corresponding pose of the assembled part are measured by the real-time stereo vision sensor. Then matrix Y, related to $m \times n$ angles of robot joint, is the output of training set, where m is the number of robot joints, and n is the number of samples; and matrix X, composed of $6 \times n$

poses of assembled part, is the input of training set. So, the input is the desired pose of assembled part, the output is the joint angle of robot we want to control.

Set a process function $f(x)$ between the input X and output Y, where x is a pose of assembled part(6×1 vector), representing one sample of X. Define its mean function $m(x) = E[f(x)]$ and its covariance function $k(x,x') = E[(f(x)-m(x)) \cdot (f(x')-m(x'))]$, where $x,x' \in R^d$ are random variables. So, we can build a Gaussian process $f(x) \sim GP(m(x),k(x,x'))$ with the above mean function and covariance function.

Taking into account the robot motion error and real-time stereo vision sensor, we set the following model:

$$y = f(x) + \varepsilon \tag{1}$$

where x is a pose of assembled part, i.e. the input value, f is a function of the value, y is a group of angles of each joint($m \times 1$ vector) , i.e. the output value, ε is the error.

Usually we assume that ε obeys the Gaussian distribution: $\varepsilon \sim N(0,\sigma_n^2)$, where σ_n^2 represents the integrated error of X and Y. So for the training set input X, we can get the prior distribution of observations Y:

$$Y \sim N(0,K(X,X)+\sigma_n^2 I_n) \tag{2}$$

where $K(X,X) = K_n = (k_{i,j})$ is a $n \times n$ covariance matrix, and $k_{i,j} = k(X_i,X_j)$ represents the correlation between the training set elements X_i and X_j. For the test input X^* , its predicted output Y^* is subject to the joint probability distribution:

$$\begin{bmatrix} Y \\ y^* \end{bmatrix} \sim N \left(0, \begin{bmatrix} K(X,X)+\sigma_n^2 I_n & K(x,x^*) \\ K(x^*,x) & k(x^*,x^*) \end{bmatrix} \right) \tag{3}$$

where $K(x,x^*) = K(x^*,x)^T$ is the covariance matrix between the test input x^* and the training set input X, and $k(x^*,x^*)$ is the covariance matrix of the test input x^*.

Then we can get the posterior distribution of y^*:

$$y^* | X,y,x^* \sim N(\bar{y}^*,\text{cov}(y^*)) \tag{4}$$

where $\bar{y}^*$ is the mean of the predicted value y^* , and $\text{cov}(y^*)$ is the variance:

$$\bar{y}^* = K(x^*,x)[K(X,X)+\sigma_n^2 I_n]^{-1} y \tag{5}$$

$$\text{cov}(y^*) = k(x^*,x^*) - K(x^*,X)[K(X,X)+\sigma_n^2 I_n]^{-1} K(X,x^*) \tag{6}$$

In the GPR model, the square exponential function is

commonly used as covariance function:

$$k(x,x') = \sigma_f^2 \exp(-\frac{1}{2}(x-x')^T M^{-1}(x-x')) \qquad (7)$$

where $M = diag(l_i^2)$, where l_i^2 is the variance scale, and σ_f^2 is called the signal variance. M, σ_f^2 and σ_n^2 form a hyper-parameter θ, which is actually a description of the input X and output Y characteristics. So the GPR model learning is to get the optimal hyper-parameter θ using the input X and output Y. Maximum likelihood is usually used for this problem.

Firstly, calculate the conditional probability $p(Y|X,\theta)$ of the training data, then calculate its negative logarithm to get the likelihood function $L(\theta) = -\log(p(Y|X,\theta))$. The partial derivatives of hyper-parameter θ is calculated further. Finally, the conjugate gradient method is performed to minimize the partial derivatives and obtain the optimal hyper-parameter θ.

The likelihood function is of the following form:

$$L(\theta) = \frac{1}{2}Y^T C^{-1} Y + \frac{1}{2}\log|C| + \frac{n}{2}\log 2\pi \qquad (8)$$

where $C = K_n + \sigma_n^2 I_n$ and the partial derivative has the following form:

$$\frac{\partial L(\theta)}{\partial \theta_i} = \frac{1}{2}tr((C^{-1}Y \cdot (C^{-1}Y)^T - C^{-1})\frac{\partial C}{\partial \theta_i}) \qquad (9)$$

Getting the optimal value of hyper-parameter, the covariance function is determined, so that for a given input we can predict the corresponding output using the above GPR model.

B. Online GPR-based kinematics compensation method

Before assembly, the real-time stereo vision, mounted on the fixed hole, measure the small-size demonstration peg assembly process to plan the optimal assembly path of the axis of moving peg. Then, large-scale peg is expected to follow the optimal assembly path generated by human demonstration. Thus, before entering into the fixed hole, the large-scale assembled peg mounted on the robot moves along a set of different poses. The poses of moving peg recorded by real-time stereo vision and corresponding joint angles of robot are picked as the training data of GPR input and output respectively; after entering into the fixed hole, the robot could predict the movement for the next step with a tiny increment until assembly process is done. If the difference of actual and predicted poses of moving peg is greater than a give threshold, the newest pair of measured pose and corresponding robot joint angle is added to GPR training data instead of the oldest pair to update accurate kinematics
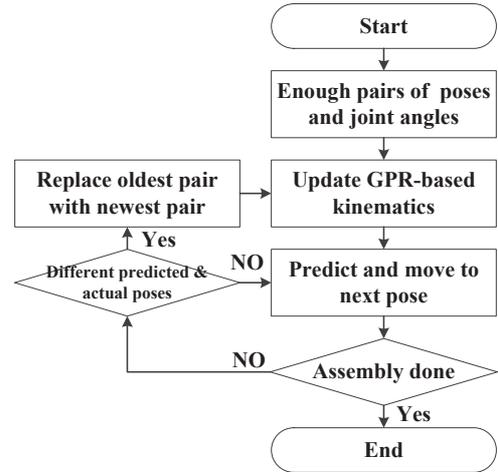

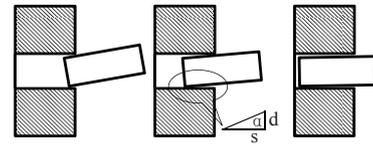Fig. 2.   Flowchart of GPR-based kinematics learning

Fig. 3.   Schematic diagram of maximum orientation tolerance

model as shown in Figure 2.

Throughout the assembly process, only GPR model is used to predict the joint angle, without involving the modeling and calculation of deformation of unknown payload and placement position. Therefore, the proposed method is of high versatility, suitable for a variety of complex systems and different load conditions, and can achieve higher control accuracy and efficiency.

IV. OPTIMAL ASSEMBLY PATH PLANNING

The robot is supposed to be able to learn some skill from the recorded data of demonstration peg assembly. In this paper, the optimal assembly path, from the initial pose to the final pose is planed from the recoded data of human demonstration. Then, the robot moves along these planed paths until final pose arrived.

Since there is no wearable force sensor for the operator, it is difficult to detect the contact state between peg and hole during human demonstration. To simple the path planning from human demonstration, the operator rotates the peg along the hole axis to keep most inclined between the moving demonstration peg and fixed assembled hole. The maximum inclined angle restricted by the fixed hole as shown in Figure 3. Obviously, the maximum inclined angle is monotonically decreased with respect to the increased distance the peg has entered into hole.

Set the distance the peg has entered into hole be s, the clearance between the peg and hole is σ, So, the maximum acceptable included angle α between the hole axis and peg axis is:

$$\alpha = \frac{\sigma}{s} \qquad (10)$$

Further, the inclined angle α_i at position i is also the function of orientations of peg axis and hole axis as:

$$v_p^i \cdot v_h = \cos(\alpha_i) \qquad (11)$$

In this case, the orientations of hole axis v_h can be determined by:

$$v_h = \left(v_p^T v_p\right)^{-1} v_p^T \cos(\alpha) \qquad (12)$$

where v_p and α are $n \times 3$ and $n \times 1$ matrices, representing the n orientations and inclined angles of peg axis at different locations. Obviously, the actual axis of the fixed hole v_h is the optimal assembly path of large-scale assembled peg.

V. EVENT-BASED CONTROL

As shown in Figure 3, the allowed maximum inclined angle is decreased with the increased distance entered into hole. Inspired from above facts, we could reach an agreement that we can speed up the movement velocity when the peg just enters into the hole and slow down the the movement velocity when the allowed inclined angle is smaller. Different from the traditional control system in terms of time, the movement velocity is expect to be a function of the distance s entered into hole. We take advantage of event-based control method for the robot during assembly to achieve a good performance with improved assembly efficiency and low risk of jamming. During assembly, the unpredictable jamming makes the assembly process immediately stops, leading to failure of time-based control. To this end, the event-based control schematic diagram of the assembly robot is shown in figure 4. The stereo vision records the distanced s entered into hole, which is regarded as the motion reference. Consequently, the desired motion velocity v in terms of s can be obtained:

$$v = \frac{c_0}{s + c_0} \qquad (13)$$

where c_0 and s_1 are predefined coefficient and the motion state q is defined as $q = (s, v)$.

Since the desired velocity is controlled by the position, the problem of time-based path planning is overcome.

VI. EXPERIMENTS

Figure 5 demonstrates the proposed robot prototype for peg-in-hole assembly based on LfD, which consists of ABB
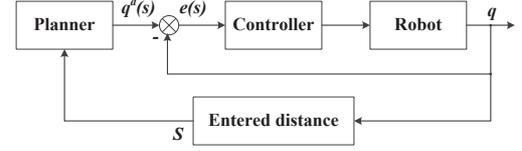

Fig. 4.   Event-based control scheme

Fig. 5.   The prototype of LfD-based assembly robot

IRB120 with IRC5 controller and a realtime stereo vision sensor mounted on the experimental platform. The robot controller and stereo vision sensor are connect to computer via Ethernet and USB3.0. The cameras of stereo vision (Manufacturer: JAI, Model: GO-5000-USB) have a resolution of 2560×2048 and are synchronized to improve measurement accuracy. To imitate the deformation caused by heavy-weight part, the weight of assembly part is close to maximum payload of robot. The fit clearance between the peg and hole is $40um$ which exceeds the absolute positioning accuracy of the industrial robot.

A. GPR-based kinematics compensation evaluation

The following experiment is performed to verify the effectiveness of the proposed GPR-based kinematics compensation method. A laser tracker is used to measure the poses of assembled part by three retro-reflectors installed on it. The laser tracker (Manufacturer: Leica, Model: AT901) as shown in Figure 6 is capable of providing 3D position of retro-reflectors with accuracy of $15um + 6um/m$ such that it is widely used for high-accuracy large-volume measurement, such as industrial robot calibration [13][14], real-time error compensation of machine tools [15], etc.

60 groups of data are randomly selected from the 80 sets of data, in which the poses are set to be the input of training data X, and the joint angles to be the output Y. Then the GPR-based kinematics compensation method is trained using these 60 groups of data. In order to validate the trained model, the remaining 20 groups of poses of assembled part

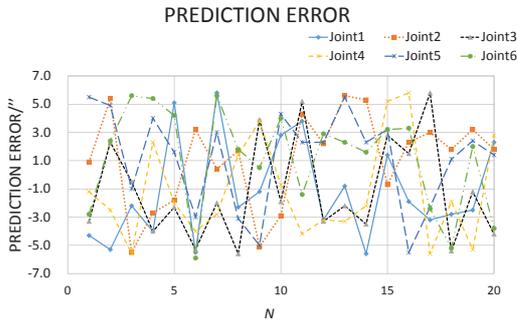Fig. 6. The laser tracker used for kinematics evaluation

Fig. 7. The predicted error of robot joint angle

Fig. 8. The position error of assembled part
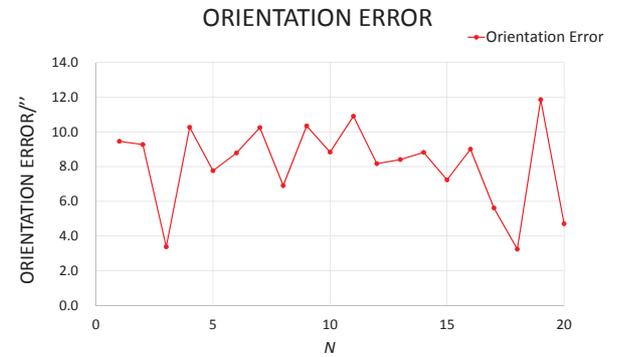
Fig. 9. The orientation error of assembled part

is set to be new input X^* and joint angles to be standard value V. Finally, the above trained GPR-based kinematics compensation method is performed to get the predicted joint angles Y^*. Now we can directly compare the predicted value Y^* and the standard value V, to get the prediction error of each joint angle as shown in Figure 7. It shows the mean value and stand deviation of the prediction error of each joint angle are round $0.003 arcsecond$, $3.6 arcsecond$, respectively.

In order to show the prediction error directly, the position and orientation of the assembled part are also predicted by the robot joint angles as shown in Figure 8, 9, respectively. The results illustrate the mean value and stand deviation of the position and orientation errors of assembled part are $7.7um$, $2.9um$, $8.2 arcsecond$, $2.4 arcsecond$, respectively. Obviously, the proposed GPR-based kinematics compensation method is capable of predicting and compensating the deformation error, resulting in improved absolute positioning accuracy. Hence, the proposed GPR-based kinematics compensation method enables the robot to realize high-accuracy movement of heavy-weight part.

B. Optimal path planning verification

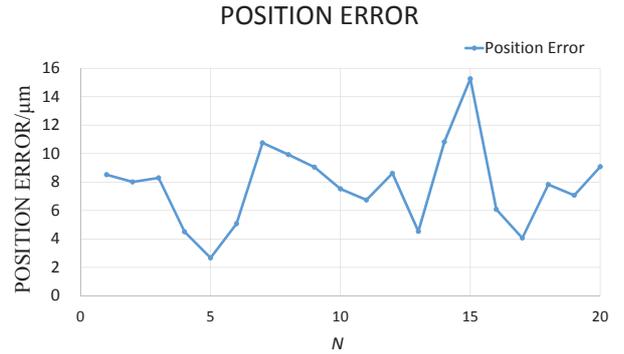The operator teaches the robot peg-in-hole assembly and the robot learns the optimal assembly path through the stereo vision sensor. The fixed hole and stereo vision sensor are mounted on the experimental platform and the demonstration peg is hold by operator and the trajectory of markers adhered to the demonstration peg are recoded by the stereo vision sensor during the demonstration procedure. The marker location in the peg coordinate frame can be measured in advance. The position and orientation accuracy of the stereo vision is verified.

The position accuracy is around $10um$ and the orientation accuracy is around $0.004°$. The operator performs the assembly task sever times and the optimal assembled path is learned by robot in the coordinate frame of stereo vision. Next, the peg is mounted on the robot end-effector to perform assembly task under the monitor of stereo vision sensor. Since the transformation matrix between stereo vision sensor and robot base is un-calibrated so that the assembled peg is expected to move along the planed assembly path in stereo vision senor as demonstration peg.

The assembly tasks performed by robot are repeated several times. The results show that the assemble part really follows the planed assembly path and the path is optimal one due to the tiny clearance between peg and hole.
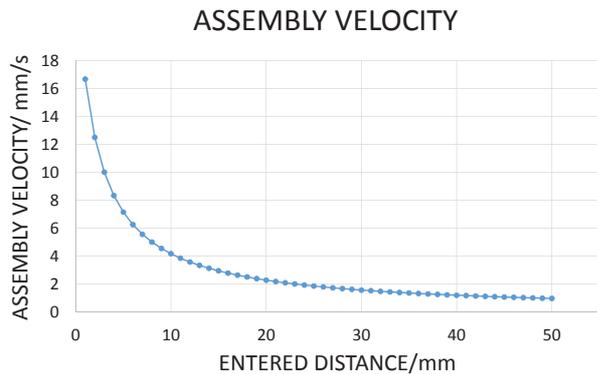
ASSEMBLY VELOCITY

Fig. 10. The movement velocity of moving peg

C. Event-based control verification

The traditional movement velocity of assembly robot is a constant, regardless of the fit tolerance, resulting in extended the assembly cycle time. To guarantee the reliability and avoid jamming, the constant velocity is very small, which is equal to the minimal velocity of our proposed method. The length of peg is $50mm$ and the fit clearance is $40um$.

Assume that the simulated assembly velocity of traditional method is $1mm/s$, then c_0 and s_1 is set to be 50 and 2 in our proposed method. So, the assembly velocity is shown in Figure 10. For traditional method, it costs around 50 seconds, whereas our proposed method costs about 27.5 seconds. Hence, the our proposed method improves the assembly efficiency and shortens assembly cycle time by more than 40%.

VII. CONCLUSION AND FUTURE WORKS

We presented a large-scale heavy-weight part assembly robotic system based on LfD in this paper. The real-time stereo vision sensor is used to record the small-size demonstration part assembly procedure by manual and the optimal assembly path is learned and planned. Then, the robot follows the planed optimal assembly path to realize large-scale heavy-weight part assembly under the monitor of stereo vision. To this end, the absolute positioning accuracy rather than repeat positioning accuracy is required in spite of the inevitable deformation caused by the heavy weight. Therefore, a GPR-based kinematics is proposed to learn accurate kinematics online and improve the absolute positioning accuracy of robot without any pre-knowledge of weight and placement position of assembly heavy-weight part. To improve the assembly efficiency, a event-based control based on the maximum tolerance of mating parts is used.

The results demonstrate that the proposed method can realize the large-scale part assembly efficiently and generate active impact in industrial applications.

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