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A Flexible Parts Assembly Algorithm Based on a Visual Sensing System

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Abstract

Unlike rigid parts, flexible parts can be deformed by contact force during assembly. For successful assembly, informations about their deformation as well as possible misalignments between the holes and their respective mating parts are essential. Such informations can be acquired from visual sensors. In case of deformable part assembly, the corrective assembly motion to compensate for such misalignments needs to be determined from the measured informations. In order to tackle these problems, authors' previous work presented a visual sensing system for measuring parts deformation in any direction and misalignments. This paper presents a visual sensor-based error-corrective algorithm using a neural network and utilizing the developed sensing system. A series of experiments to compensate for the lateral misalignment are performed. The experimental results show that the proposed sensing system and the error-corrective algorithm are effective in the assembly tasks of deformable parts, thereby dramatically increasing the rate of success in assembly operations.

Key words : Flexible parts assembly, Visual sensing system, Error-corrective algorithm, Part deformation, Misalignment, Neural network

1. Introduction

For successful assembly of flexible parts, informations about their deformation as well as possible misalignments between the holes and their respective mating parts are essential. However, because of the nonlinear and complex relationship between parts deformation and reaction forces, it is difficult to acquire all required informations from the reaction forces alone. Such informations can be acquired from visual sensors. Therefore, visual sensors are widely used in such tasks as assembly or handling of flexible parts. Compared with a variety of research in the area of rigid parts assembly [1], not much research has been done on flexible parts assembly [2]. In addition, none of the above works measured both of parts deformation and misalignment between the mating parts. Flexible parts assembly, however, requires three-dimensional measurement of parts deformation as well as misalignments between the occluded holes and their respective mating parts. Previously, the authors have presented a visual sensing system that can detect three-dimensional part deformation and misalignment [3]. And the authors have presented an algorithm to measure parts deformation and misalignments by using the sensing system in cylindrical peg-in-hole tasks [4].

In robotic assembly of flexible parts, the relationship between the measured informations on misalignment or part deformation and the corrective assembly motion becomes very complex, thus making its theoretical analysis not easy. Therefore, in case of flexible parts handling including assembly tasks, an AI-based method is frequently used. The authors have presented a neural net-based error-corrective algorithm that extracts the robotic corrective motion by using the information obtained from the visual sensing system [5]. In this paper, a series of experiments to compensate for the lateral misalignment are performed. The purpose of this experimental works is to evaluate the effectiveness of the developed visual sensing system and the assembly algorithm.

This paper is organized as follows: In section 2, the principle and the configuration of the visual sensing system are described. In section 3, the algorithm to measure parts deformation and misalignment is described. In section 4, a neural net-based error-corrective algorithm to compensate for lateral misalignment is described. In section 5, a series of experiments for misalignment compensation are performed. The experimental results and discussions are described. Finally, some conclusions are made in section 6.

2. A Visual Sensing System

Fig. 1(a) illustrates the basic configuration of the sensing system. It is composed of a camera, a pair of plane mirrors, and a pair of pyramidal mirrors. In order to measure three-dimensional deformation by using a camera, two views are necessary, as shown in Fig. 1(b). Fig. 1(c) illustrates an image of a peg and a hole pair. Because four images that are reflected from each face of the pyramidal mirrors are projected onto the image plane of a camera, this system configuration is equivalent to that utilizing four cameras. This configuration allows the system to overcome self-occlusion. The design and implementation method has been presented in the previous work [3].

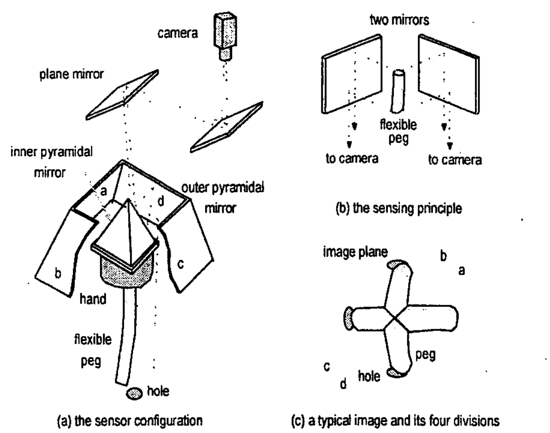

Fig. 1. The schematic of the sensing system

3. An Algorithm to Measure Part Deformation and Misalignment

In order to assemble the flexible parts successfully, parts deformation in any direction and misalignments between mating parts need to be measured. In this section, the algorithm to estimate parts deformation and misalignments by using a visual sensing system in cylindrical peg-in-hole tasks is described. Parts deformation can be represented by the shape of the center-line of a peg. Misalignment between mating parts is defined as the relative error between the center of a hole and the center of the bottom of a peg.

In the case of a cylindrical peg with a circular cross-section, it can be assumed that its center-line is projected to the center-lines of its projected images [6]. Thus, parts deformation can be obtained by estimating the center-lines in two-dimensional peg images.

3.1. Estimation of Part Deformation

To estimate parts deformation, pegs must first be recognized in edge images. Their edges are extracted in the images taken by the proposed system, and classified into the sides and the bottoms of peg. The two center-lines in the images are then extracted. A center-line is composed of the midpoints between two side edges in one image. Next, corresponding points in two center-lines are found using epipolar constraint. Finally, from corresponding points, the center-line of a peg is reconstructed in three-dimensional space. Fig. 2 shows the flow chart of the algorithm to estimate deformation of a cylindrical peg.

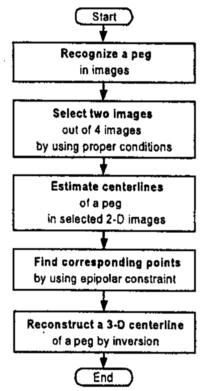

Fig. 2. Algorithm to estimate the deformation of a cylindrical peg

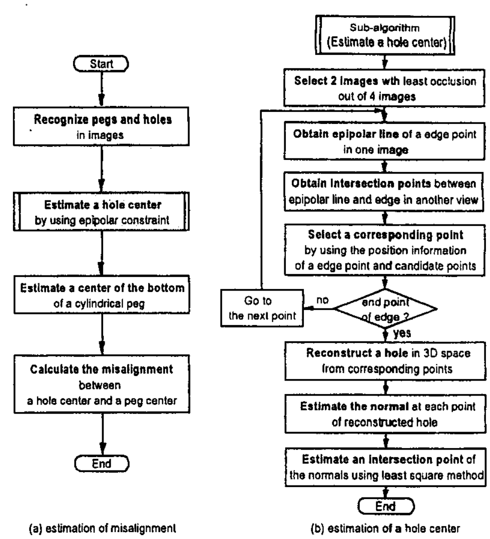

Fig. 3. Algorithm to estimate misalignment

3.2. Estimation of Misalignment

To estimate misalignments between the holes and their respective mating parts, the center of an occluded hole and the center of the bottom of a peg are evaluated. First, pegs and holes in images are recognized. Next, the center of an occluded hole is found using epipolar constraint. Next, the center of the bottom of a peg is found by using the same method. Finally, misalignment is calculated from the difference between a hole center and a peg center. Fig. 3 shows the flow charts of the algorithm to estimate misalignment and to estimate the center of an occluded hole.

4. A Vision-Based Error-Corrective Algorithm

4.1. Simplified Relationship between Misalignment and Its Corrective Motion

In order to obtain the relationship between misalignment and its corrective motion which is available for all tasks in flexible parts assembly, all of the related parameters have to be considered. The related parameters are the six components of the assembly errors and the six components of the error-corrective motion [5]. However, the relationship among them is very complex. Besides, some parameters are difficult to find out their accurate values. Therefore, it is of advantage to obtain the simplified relationship related to only some parameters through several assumptions. Based on it, the general relationship that is available for more general tasks will be able to be obtained by considering more parameters. The simplified relationship will be obtained through following assumptions.

a) Only one kind of part with the same properties and size is dealt with. Accordingly, the flexural rigidity EI is constant.
b) By setting the z-position of a robot uniformly during misalignment compensation, the reaction forces are maintained constantly.
c) It is established that the upper end of the part is fixed, and that its lower end is free. Accordingly, the boundary conditions C_{bc} are constant.
d) The deformation shape of a part is uniform if its boundary conditions and the positions of its both ends are the same. Namely, the number of deformation mode is one.
e) During misalignment compensation, the misalignment and the corrective motion which are related to the z-direction can be neglected. In other words, only the misalignment and the corrective motion on the horizontal plane are considered.
f) The part to be assembled is generally deformed toward the center of its mating hole.

By above six assumptions, the components to be considered are just the corrective motion m^r_e, $m^r_{\phi_h}$ and the misalignment e_m, ϕ_h, θ_v, as shown in Fig. 4. The simplified relationship among them is expressed by

$$\begin{bmatrix} m^r_e \\ m^r_{\phi_h} \end{bmatrix} = f_s\left(\begin{bmatrix} e_m \\ \phi_h \\ \theta_v \end{bmatrix}\right) \tag{1}$$

It is difficult to find out the perfect relationship of Eq. (1) due to its complexity and nonlinearity. Accordingly, it is advised to take advantage of the theory of artificial intelligence(AI).

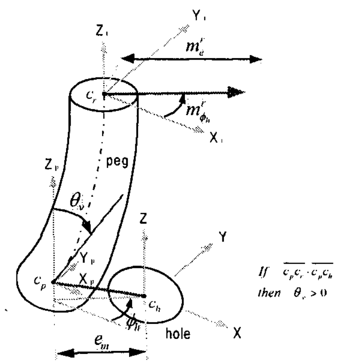

Fig. 4. Misalignment and corrective motion in simplified relationship

4.2. An Error-Corrective Algorithm

Fig. 5 shows the block diagram of the neural net-based error-corrective algorithm. The assembly strategy is focused on how to find out the relations between the measured information $[e_m, \phi_h, \theta_v]^T$ obtained from the visual sensor only and the corrective motion $[m^r_e, m^r_{\phi_h}]^T$. This algorithm can be applied to the assembly tasks which satisfy the assumptions described in section 4.1. However, its concept will be able to be extended to more general tasks.

It is assumed heuristically that the direction $m^r_{\phi_h}$ of a corrective motion is equal to the azimuth angle ϕ_h of the misalignment. Consequently, Eq. (1) can be divided into two equations, which are given by

$$m^r_e = f_n\left(\begin{bmatrix} e_m \\ \theta_v \end{bmatrix}\right) \tag{2}$$

$$m^r_{\phi_h} = \phi_h \tag{3}$$

where e_m, θ_v, ϕ_h are measured by the visual sensing system, and the corrective action m_c^r is estimated by the neural network.

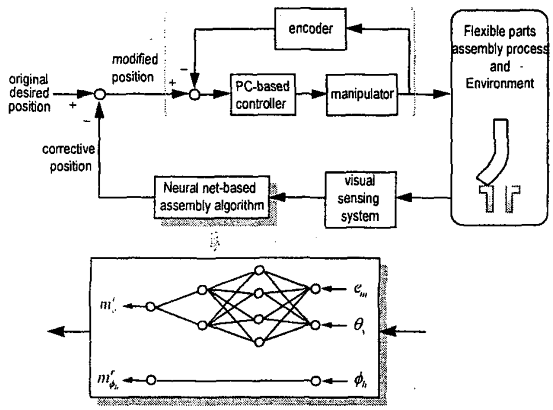

Fig. 5. The block diagram of the neural net-based assembly algorithm

This paper implements a multilayer feedforward network which has 2-4-2-1 nodes. Forty two sets of the input and output variables e_m, θ_v, m_c^r were selected as the training samples. Cylindrical urethane pegs were used in these experiments. They are 10 *mm* in diameter, and 60 *mm* long. The error backpropagation using the generalized delta rule is used to train the network.

5. Experiments for Misalignment Compensation

5.1. Experimental System

To investigate the effectiveness of the proposed error-corrective algorithm, a series of experiments for misalignment compensation are performed. Fig. 6 shows the schematic diagram of the experimental system. The system consists of a SCARA robot, the visual sensing system, a vision board, a PC-based robot controller, and so on. The PC-based robot controller generates the control signals for actuating a robot manipulator by using the informations measured by the visual sensing system, and by using the corrective motion estimated by the neural network. In these experiments, the cylindrical urethane pegs with diameter d_p of 10.0 mm and the aluminium hole with diameter d_h of 10.53 mm.

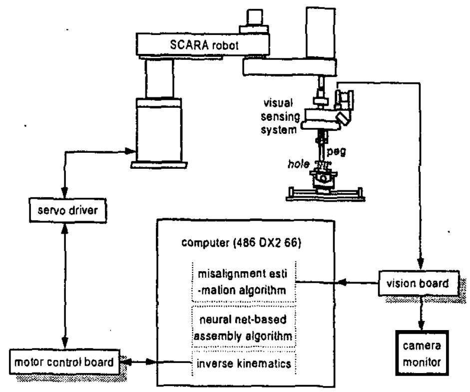

Fig. 6. Schematic diagram of the experimental set-up

The experiments to compensate for lateral misalignment were mainly performed. Also the experiments to compensate for the inclination error of a part and to insert a part into its mating hole were performed.

5.2. Results and Discussions

Fig. 7(a) shows the experimental results when $e_m = 1$ mm and $c_r = -2, 1, 4$ mm. The e_m denotes initial lateral misalignment, while the c_r denotes the center position of the upper surface of a part. When e_m is small, the error in estimating a hole center using the implemented visual sensing system becomes large because the visible area of the hole is very small [4]. Figs. 7(a1) and (a2) show large error between the prescribed value and the value measured by the sensing system in estimating a hole center. When $c_r = 1, -2$ mm, the lateral misalignment was compensated by one corrective motion. When $c_r = 4$ mm, it was compensated by two times of corrective motion. The magnitude of the corrective motion estimated from the neural network is not equal to that of the actual corrective motion until misalignment compensation is actually accomplished. Also, the direction of the corrective motion is not consistent with the actual direction toward the hole center because of the measurement error by the visual sensing system. Nevertheless, the lateral misalignment was compensated successfully. This is due to the sufficient clearance between a part and its mating hole, which is larger than the estimation error or the measurement error. Another reason is that initially fitted part into its mating hole does not escape easily from the hole due to its deformation although the corrective motion is going on.

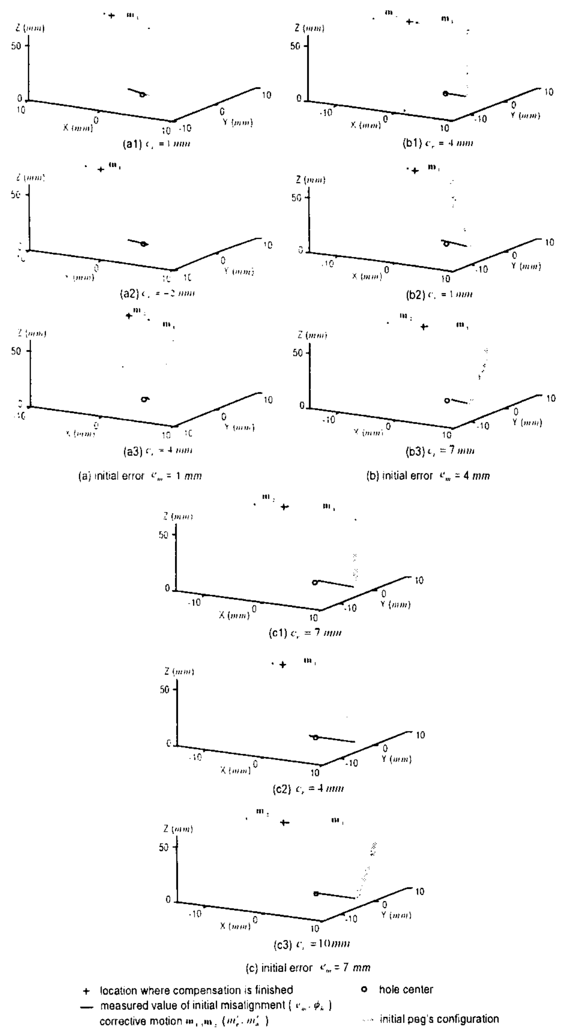

Fig. 7. Experimental results for misalignment compensation

Fig. 7(b) shows the experimental results when $e_m = 4$ mm and $c_r = 1, 4, 7$ mm. The error between the prescribed value and the measured value of e_m, and the error between the estimated corrective motion and the actual corrective motion until misalignment compensation is actually accomplished are not large compared with those of the case $e_m = 1$ mm in Fig. 7(a). When $c_r = 1$ mm, the lateral misalignment was compensated by one corrective motion inferred from the neural network. When $c_r = 4$, 7 mm, the lateral misalignment was compensated by two times of corrective motion. Misalignment compensation was accomplished at the beginning of the second corrective motion, because the difference between the estimated motion and the actual motion is not large in the first corrective motion $\mathbf{m}_1$. However, there is quite large difference in the second corrective motion $\mathbf{m}_2$. This is due to the same reason as for the case $e_m = 1$ mm in Fig. 7(a) because the bottom of the peg was moved near to the hole by $\mathbf{m}_1$. On the other hand, this successful compensation does not guarantee success in more general tasks such as high speed or high precision assembly. However, success rate of misalignment compensation in such tasks will be increased by considering more assembly relevant parameters in a neural net-based estimation system.

Fig. 7(c) shows the experimental results when $e_m = 7$ mm and $c_r = 4, 7, 10$ mm. Both the measurement error of e_m by the sensing system and the error in the estimated corrective motion are not large. When $c_r = 7$, 10 mm, two times of corrective motion was required to compensate for the lateral misalignment. It was compensated at the beginning of the second corrective motion. These results are similar to those in Fig. 7(b).

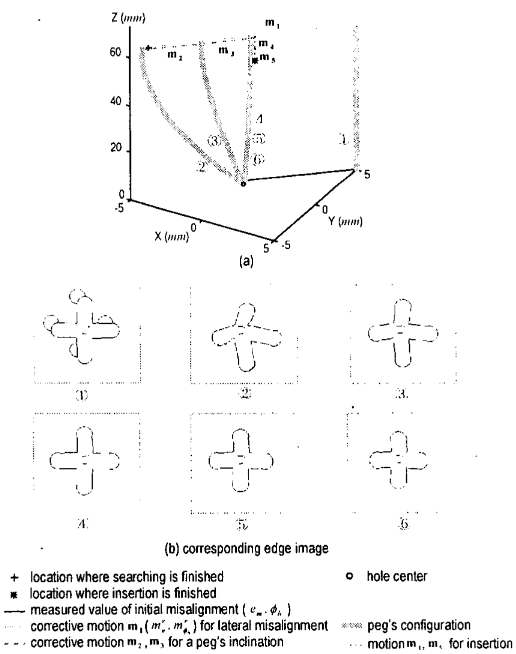

Fig. 8. Experimental results for insertion into hole ($e_m = 7$ mm, $c_r = 7$ mm, $\phi_h = 45°$)

Fig. 8 shows the experimental results when $e_m = 7$ mm, $c_r = 7$ mm and $\phi_h = 45°$. The ϕ_h denotes the direction of lateral misalignment. The lateral misalignment in the state ① was compensated to the state ② by the first corrective motion $\mathbf{m}_1$. The inclination error in the state ② was also compensated to the state ④ by the subsequent corrective motion $\mathbf{m}_2$, $\mathbf{m}_3$. The states ⑤ and ⑥ show the part inserted into its mating hole by the robot motion $\mathbf{m}_4$, $\mathbf{m}_5$. Through these experiments, it was confirmed that the inclination error due to part deformation can be compensated even by the translational corrective motion alone, and that a part can be inserted into its mating hole after the lateral and inclination error are compensated. Fig. 8(b) shows the edge images of the part and its mating hole obtained by the visual sensing system from the states ① to ⑥.

From these results, it is confirmed that the proposed neural net-based error-corrective algorithm is efficient not only for lateral misalignment compensation, but also for inclination error compensation. And the similar concept will be able to be extended to the insertion process into a hole.

6. Conclusions

This paper presented a visual sensing system and an algorithm for measuring parts deformation and misalignments in cylindrical peg-in-hole tasks. And it proposed an error-corrective algorithm that can compensate for the misalignment between a part and its mating hole, based on the measured informations. With a simplified neural network-based estimation system under several assumptions, the training and performance verification of the network were performed. It was heuristically determined that the direction of the corrective motion is equal to that of misalignment. Finally, a series of experiments for misalignment compensation were performed.

From these results, it is concluded that the sensing system and the error-corrective algorithm are efficient for misalignment compensation in flexible parts assembly. The algorithm will be able to be extended to more general tasks such as high speed or high precision assembly by taking into consideration more parameters as the inputs or outputs of the neural network. Further work will be made in this regard.

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