Autonomous Hole Search and Insertion Compensation for Peg-in-hole Assembly Task Using Robotic Arm

Shih-Kang Chen, *Member, IEEE*, Chin-Sheng Chen, *Member, IEEE,* I-Ching Li and Fung-Chi Lee

***Abstract*— This paper aims to discuss the state-of-the-art technique for autonomous peg-in-hole assembly tasks. The peg-in-hole process includes two stages: hole search and insertion compensation. In the hole search stage, machine vision is introduced to detect the hole position and the contact force combined with the contact model to estimate the hole position. The analytical model, impedance control, and machine learning with insertion compensation are present in the insertion compensation. The pros and cons of the introduced method are further discussed in the discussion section.**

***Index Terms*—Autonomous robotic systems, Intelligent robotics, Robotics technology, System analysis and optimization, Machine learning in modeling, prediction, control and automation, Smart assembly, Smart manufacturing**

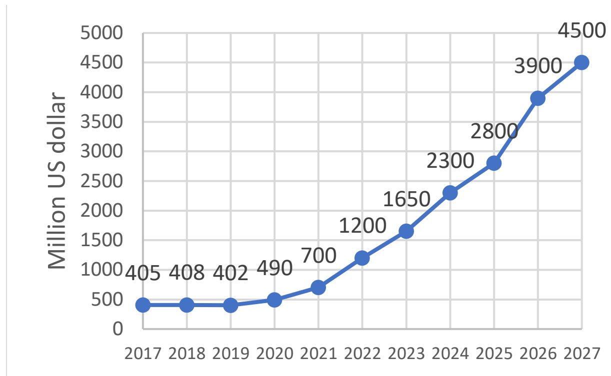

Fig. 1 Global Collaborative Robot Marketing Statistics and Forecast

I. Introduction

Due to the aging population issue in recent years in Taiwan, the government has started to fund research institutions, universities and companies to develop the autonomous assembly system and further uses for production. Therefore, machine learning algorithms and robotic systems have become popular research topics [1].

The peg-in-hole assembly is the most common assembly task for a robotic arm. The research also shows that the demand for the collaborative robot has been growing recently, as shown in Fig. 1. Furthermore, the peg-in-hole assembly using a collaborative robot to co-work with the human operator has become customary in a factory. Typically, the peg-in-hole task can be separated into two stages: searching for a hole and inserting the peg. In the searching hole stage, machine vision can accurately detect the relationship between the hole and peg by eye-in-hand and eye-to-hand camera. Without the machine vision system, the intuitive assembly strategy of the move following the spiral trajectory or some specifically designed trajectory can be applied. Then, the contact force/torque can be analyzed to estimate the hole location after the previously introduced methodology finds the hole, the center axis of the peg and the hole still hard to align. Therefore, the axial friction reduction and compliance insertion methods are applied to improve the assembly quality during the peg-in-hole process.

In a more in-depth study, the F/T sensor is used to determine the contact F/T between a robot's end-effector and a hole and for analysis or compensation [2-4]. In terms of contact F/T compensation studies, Wang used a neural network model to predict the contact F/T and used this for compensation [5]. Xu and Hou used a fuzzy logic-driven compensator with deep learning skills to compensate the F/T during a peg-in-hole process [6, 7]. The computational power of computers has been growing faster recently, so deep learning neural networks and reinforcement learning policies are used for an F/T compensator for high-precision robotic assembly tasks [8-11]. Zhang used compliance control with fuzzy control and force feedback to improve the assembly strategy [12]. Zou used a wrist force sensor to measure the external force on the load and used an impedance controller with velocity control to minimize environmental contact [13]. To address non-alignment, Liu used axial friction with an analytical method to optimize the assembly [14]. Reinforcement learning (RL) is a novel technology used to generate the model based on rewarding desired behaviors and/or punishing undesired ones. The InsertionNet is proposed by Spector to solve the insertion problem using RL [15]. Wang used RL to shape exploration space due to the contact model of the object for insertion is uncertain [16].

This paper discusses the autonomous hole search and active insertion compensation technique. The authors have published some research articles on this issue. Our team is working-in-process to improve the performance and quality

S.-K. Chen is with the Department of Mechatronics Control, Industrial Technology Research Institute, Hsinchu, Taiwan. (e-mail: jimmy4920@gmail.com)

C.-S. Chen is with the Institute of Automation Technology, National Taipei University of Technology, Taipei, Taiwan (e-mail: saint@mail.ntut.edu.tw)

I.-C. Li is with the Department of Mechatronics Control, Industrial Technology Research Institute, Hsinchu, Taiwan. (e-mail: grace950026@gmail.com)

F.-C. Lee is with the Department of Mechatronics Control, Industrial Technology Research Institute, Hsinchu, Taiwan. (e-mail: lifengchi@itri.org.tw)

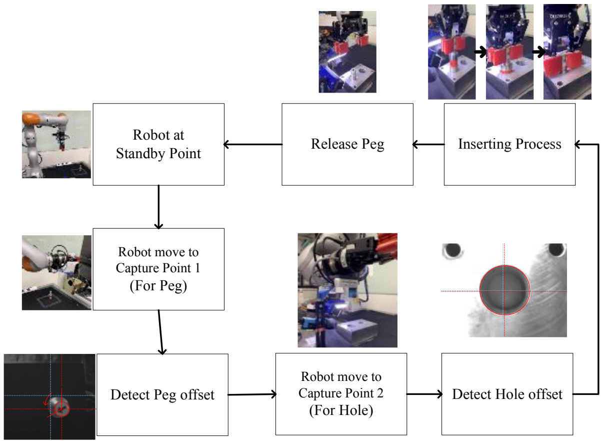

Fig. 2 A flowchart for the machine vision-based peg-in-hole task

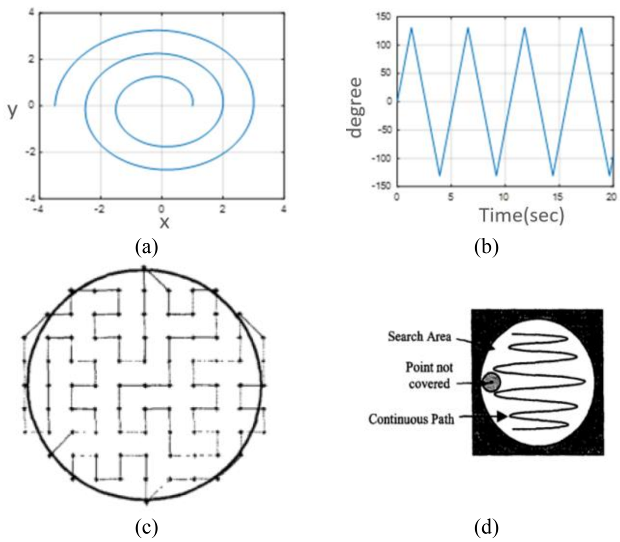

Fig. 3 The trajectories for hole search: (a)the spiral trajectory for xy axis, (b)the rotation angle about x-axis follows above trajectory, (c)specifically designed trajectory and (d)searching trajectory for contact force detection

of the high-precision peg-in-hole assembly task.

II. Hole Search Strategies

The hole search strategies can be simply machine vision-based and contact-based methods. The details will be introduced in the following sections. After the hole has been found, the peg-in-hole process will insert the peg into the hole via the insertion strategies.

A. Machine vison-based hole search

The machine vision system can be used to estimate the 2-dimension and 3-dimension position and orientation of the object in the image depending on the camera system. A flow of a peg-in-hole task with eye-in-hand machine vision correction is shown in Fig. 2. The robotic arm first moves to capture point 1 to capture and detect the peg location by image recognition algorithm. After the robot picks up the object, the robot system will command the robotic arm to capture point 2 to detect the hole offset. Finally, the relationship between the peg and hole can be estimated by the aforementioned flow.

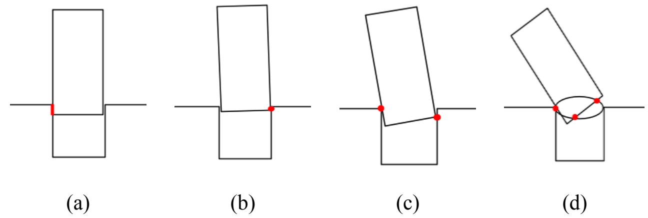

Fig. 4 Alignment condition between peg and hole before insertion: (a) line contact, (b)One-point contact, (c)Two-point contact and (d) Three-point contact.

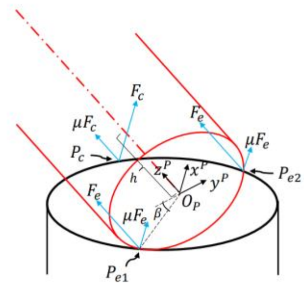

Fig. 5 Geometric Analysis of three-point contact

B. Contact force-based hole search

The contact force-based hole search method usually uses contact force between the robot end-effector and the contact plane to estimate the hole location. Furthermore, a specifically designed trajectory [17], such as a spiral trajectory [18], is used to generate contact force for the search algorithm, shown in Fig. 3. The following figures displace the designed trajectory, which is used to generate the contact force.

III. Insertion Strategies

In the peg-in-hole task, the robot system will first grasp the peg and detect the hole location by the previously detailed strategy. After that, the insertion is also an important issue during the assembly task. If the center axis of the hole and the peg are not aligned, the assembly task will not succeed during the insertion. As a result, improving the assembly success rate become a capstone in the task. The analytical method and machine learning-based algorithm are applied to optimize the result to find the correct angle and position for the robot end-effector.

A. Analytical method for insertion correction

The correction of the insertion using the analytical method usually combine with the force/torque feedback. In this scenario, the robotic arm needs to maintain the contact situation, as shown in Fig. 4. Once the contact model is maintained, the contact force model can be derived [19]. One of the three-point contact models is shown in Fig. 5. Therefore, the tilt angle is able to be estimated by combining it with the force/torque feedback.

B. Impedance control method for insertion correction

Instead of using an analytical method to estimate the tilt angle of the peg, the insertion correction can combine with the impedance control. Park et al. designed a partial spiral force

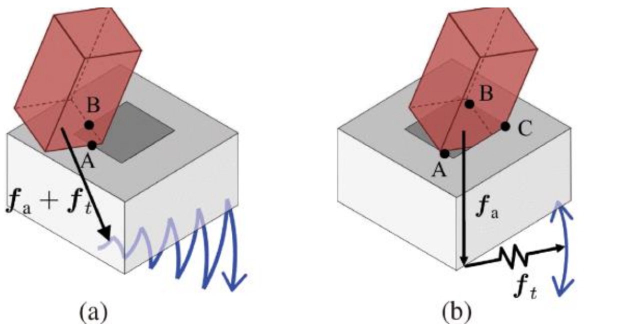

Fig. 6 Assembly force and force generated by PSFT: (a) two-point contact and (b) three-point contact.

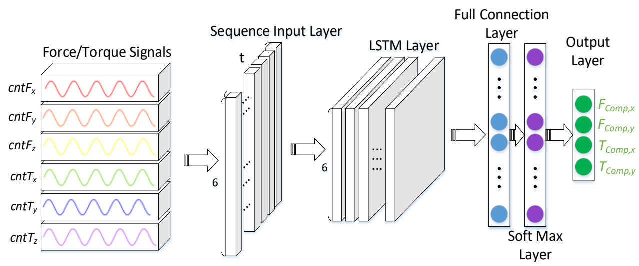

Fig. 7 The LSTM for estimating the compensation force/torque.

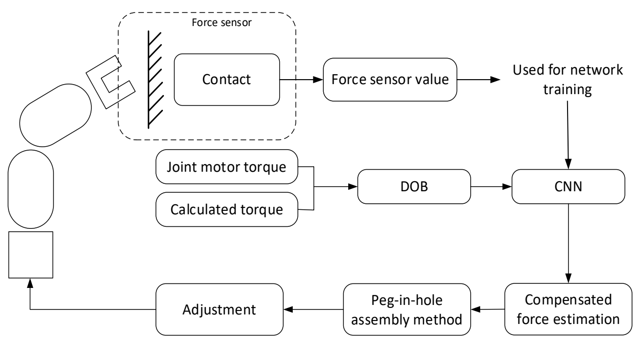

Fig. 8 The compensation flow for insertion combines with the CNN.

trajectory (PSFT) with an impedance control method [20], shown in Fig. 6. The end-effector moves following the trajectory and corrects the attitude using impedance control. The proposed method is more effective than the analytical method.

C. Machine learning for insertion compensation

Since the computation power of a computer is growing, the complex machine learning-based method with large computation consumption can be utilized in robotics. The authors applied the LSTM to model the contact pattern during insertion to estimate the compensation force and torque, as shown in Fig. 7 [21]. A convolutional neural network (CNN) was implemented in the compensation flow to estimate the correction by Zhang [12], as shown in Fig. 8. The reinforcement learning for insertion was implemented by Luo, as shown in Fig. 9 [22]. The results show that machine learning can improve the assembly quality for peg-in-hole tasks. Furthermore, RL is widely used to improve assembly quality. Dong used RL to generate the object geometry with contact force [23]. Shi considered incorporating operational space visual and haptic into RL to solve the target uncertainty problem [24]. Xu combined the manipulation primitives,

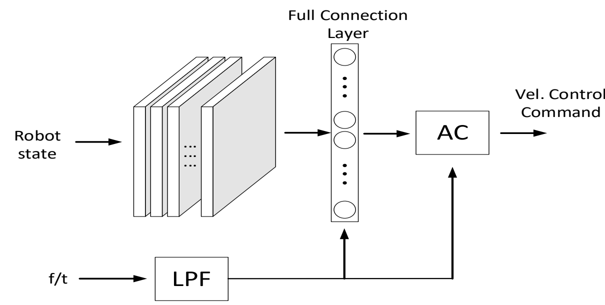

Fig. 9 The compensation network for insertion combines with the reinforcement learning.

behavior tree and RL with speeding up the convergence of the RL model [25].

IV. Discussion

A. Hole Search

Machine vision and contact force search are the common search strategies applied for hole search. The machine vision-based search algorithm is much more accurate than the contact force search and not necessary to derive the mathematical model. Furthermore, the contact force-based search constrains the relationship between peg and hole in the designed searching trajectory. On the other hand, the machine vision system increased the cost of the vision system and applied the image processing technique with the peg-in-hole process.

B. Active Insertion Strategies

The analytical model, impedance control and machine learning with insertion compensation were introduced. The analytical model has to maintain the contact model and then uses the contact force/torque and the following model to estimate the compensation position and orientation. The impedance control uses the compliance model to insert the peg and correct the angle during insertion, which is more effective than the analytical model. However, the compliance control will decrease accuracy and fail due to the initial bias for the peg over the compensation limit. Finally, the machine learning model is applied to estimate in addition forecast the correction during insertion. Nevertheless, the machine learning model consumes more computation to calculate the compensation value.

V. Working-in-process Case

The authors have published some research articles to discuss the peg-in-hole issue using the cylinder peg [21]. The industrial technology research institute (ITRI) aims to support the industry's development. Therefore, our team is working-in-process to enhance the performance and quality of the peg-in-hole process using deep learning techniques. Furthermore, our team is working toward improving the insertion quality with different shapes of the object, such as: Universal Serial Bus(USB) port, Ethernet port, square shape and irregular shape.

VI. Conclusion

In recent years, the pandemic has caused a labor shortage. Therefore, smart manufacturing using robotic systems has become a popular topic. This paper discusses the autonomous hole search and insertion compensation for peg-in-hole assembly tasks using a robotic arm. The peg-in-hole process includes two main stages: hole search and insertion compensation. The state-of-the-art algorithms are introduced, and the pros and cons are compared in the discussion. As a non-profit organization, the ITRI is currently researching critical technologies for smart manufacturing and artificial intelligence for manufacturing. Our goal is to support the development of the industry. We are presently working-in-process to develop an intelligent assembly system using a robotic arm.

Acknowledgment

This study was financial sponsored by the Ministry of Science and Technology, Taiwan, R.O.C., under the project No. MOST 109-2221-E-027-044-MY3

References

[1] H. J., *Development of Servo Motors for Collaborative Robots In the age of Artificial Intelligence*, IEKConsulting, 2022.

[2] J. Luo, E. Solowjow, C. Wen, J. A. Ojea, and A. M. Agogino, “Deep Reinforcement Learning for Robotic Assembly of Mixed Deformable and Rigid Objects,” in *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2018.

[3] R. C. Luo, A. Chang, and L. Cheng, “A novel peg-in-hole approach based on geometrical analysis for inclined uncertainty,” in *2017 IEEE International Conference on Advanced Intelligent Mechatronics (AIM)*, 2017.

[4] B. Chen, Y. Wang, and P. Lin, “A Feedback Force Controller Fusing Traditional Control and Reinforcement Learning Strategies,” in *2019 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM)*, 2019.

[5] Y. Wang, P. Wang, C. Liu, G. Hao, Z. Xiong, X. Quan, X. Yuan, and H. Zhou, “Contact Force/Torque Prediction and Analysis Model for Large Length-diameter Ratio Peg-in-hole Assembly,” in *2018 IEEE International Conference on Robotics and Biomimetics (ROBIO)*, 2018.

[6] J. Xu, Z. Hou, W. Wang, B. Xu, K. Zhang, and K. Chen, “Feedback Deep Deterministic Policy Gradient With Fuzzy Reward for Robotic Multiple Peg-in-Hole Assembly Tasks,” *IEEE Transactions on Industrial Informatics,* vol. 15, no. 3, pp. 1658-1667, 2019.

[7] Z. Hou, Z. Li, C. Hsu, K. Zhang, and J. Xu, “Fuzzy Logic-Driven Variable Time-Scale Prediction-Based Reinforcement Learning for Robotic Multiple Peg-in-Hole Assembly,” *IEEE Transactions on Automation Science and Engineering,* vol. 19, no. 1, pp. 218-229, 2022.

[8] T. Inoue, G. D. Magistris, A. Munawar, T. Yokoya, and R. Tachibana, “Deep reinforcement learning for high precision assembly tasks,” in *2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2017.

[9] X. Wu, D. Zhang, F. Qin, and D. Xu, “Deep Reinforcement Learning of Robotic Precision Insertion Skill Accelerated by Demonstrations,” in *2019 IEEE 15th International Conference on Automation Science and Engineering (CASE)*, 2019.

[10] Z. Hou, J. Fei, Y. Deng, and J. Xu, “Data-efficient Hierarchical Reinforcement Learning for Robotic Assembly Control Applications,” *IEEE Transactions on Industrial Electronics*, pp. 1-1, 2020.

[11] J. Luo, E. Solowjow, C. Wen, J. A. Ojea, A. M. Agogino, A. Tamar, and P. Abbeel, “Reinforcement Learning on Variable Impedance Controller for High-Precision Robotic Assembly,” in *2019 International Conference on Robotics and Automation (ICRA)*, 2019.

[12] Z. Zhang, Z. Fang, H. Lian, C. Zhang, and G. Yang, “Robotic Peg-in-Hole Assembly System Based on Vision and Fuzzy Control,” in *2021 Chinese Control and Decision Conference*, Kunming, China, 2021.

[13] P. Zou, Q. Zhu, J. Wu, and J. Jin, “An Approach for Peg-in-Hole Assembling Based on Force Feedback Control,” in *2019 Chinese Automation Congress*, Hangzhou, China, 2019.

[14] Z. Liu, L. Song, Z. Hou, K. Chen, S. Liu, and J. Xu, “Screw Insertion Method in Peg-in-Hole Assembly for Axial Friction Reduction,” *IEEE Access,* vol. 7, pp. 148313-148325, 2019.

[15] O. Spector, and D. D. Castro, “InsertionNet - A Scalable Solution for Insertion,” *IEEE Robotics and Automation Letters,* vol. 6, no. 3, pp. 5509-5516, 2021.

[16] C. Wang, C. Lin, B. Liu, C. Su, P. Xu, and L. Xie, “Deep Reinforcement Learning with Shaping Exploration Space for Robotic Assembly,” in *2021 3rd International Symposium on Robotics & Intelligent Manufacturing Technology (ISRIMT)*, 2021.

[17] S. R. Chhatpar, and M. S. Branicky, “Search strategies for peg-in-hole assemblies with position uncertainty,” in *Proceedings 2001 IEEE/RSJ International Conference on Intelligent Robots and Systems. Expanding the Societal Role of Robotics in the the Next Millennium (Cat. No.01CH37180)*, 2001.

[18] P. Hyeonjun, B. Ji-Hun, P. Jae-Han, B. Moon-Hong, and P. Jaeheung, “Intuitive peg-in-hole assembly strategy with a compliant manipulator,” in *IEEE ISR 2013*, 2013.

[19] T. Tang, H. Lin, Y. Zhao, W. Chen, and M. Tomizuka, “Autonomous alignment of peg and hole by force/torque measurement for robotic assembly,” in 2016 IEEE International Conference on Automation Science and Engineering (CASE), Fort Worth, Texas, USA, 2016.

[20] H. Park, J. Park, D. H. Lee, J. H. Park, and J. H. Bae, “Compliant Peg-in-Hole Assembly Using Partial Spiral Force Trajectory With Tilted Peg Posture,” *IEEE Robotics and Automation Letters,* vol. 5, no. 3, pp. 4447-4454, 2020.

[21] S.-K. Chen, “A Brain-Computer Interface based Human-Robot Collaborative Autonomous Assembly System,” Institute of Mechanical and Electrical Engineering, National Taipei University of Technology, 2021.

[22] J. Luo, E. Solowjow, C. Wen, J. A. Ojea, and A. M. Agogino, “Deep Reinforcement Learning for Robotic Assembly of Mixed Deformable and Rigid Objects,” in *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems*, Madrid, Spain, 2018.

[23] S. Dong, D. K. Jha, D. Romeres, S. Kim, D. Nikovski, and A. Rodriguez, “Tactile-RL for Insertion: Generalization to Objects of Unknown Geometry,” in *2021 IEEE International Conference on Robotics and Automation (ICRA)*, 2021.

[24] Y. Shi, Z. Chen, H. Liu, S. Riedel, C. Gao, Q. Feng, J. Deng, and J. Zhang, “Proactive Action Visual Residual Reinforcement Learning for Contact-Rich Tasks Using a Torque-Controlled Robot,” in *2021 IEEE International Conference on Robotics and Automation (ICRA)*, 2021.

[25] A. Graves, "Generating sequences with recurrent neural networks," *arXiv preprint arXiv:1308.0850*, https://arxiv.org/abs/1308.0850, 2013].