Design and Control of Advanced Robotic Systems for Manufacturing and Assembly

Deepak Verma
Asst. Professor, Department of Mechanical Engineering, Graphic Era Hill University, Dehradun Uttarakhand India

Article Info
Page Number: 540-550
Publication Issue:
Vol. 70 No. 1 (2021)

Abstract
Modern industrial processes must now be designed and controlled with advanced robotic systems for manufacture and assembly to increase productivity, accuracy, and flexibility. The main factors involved in creating and overseeing these robotic systems are presented in detail in this work.In the design stage, manipulators, sensors, and end-effectors that are customised for the particular manufacturing or assembly task are chosen and integrated. To ensure accurate and efficient task execution, additional control algorithms and programming techniques are also developed. This covers adaptive control techniques, path optimisation, trajectory planning, and collision avoidance.The real-time monitoring, coordinating, and synchronisation of several robots and their interactions with the environment are the main goals of the control component. The integration of human operators with robotic systems is made possible by centralised or decentralised control frameworks, which promote secure and effective production and assembly procedures.The study also discusses how to improve robotic systems' abilities to handle complicated jobs and adapt to shifting production settings by integrating cutting-edge technologies like machine learning, computer vision, and augmented reality.The difficulties and possibilities posed by the application of sophisticated robotic systems for manufacturing and assembly are also covered. These include the dependability of the system, the ethical effects of automation in the workplace, the detection and recovery of faults, and human-robot collaboration.The ultimate goal of this work is to give readers a thorough grasp of the design and control principles required for creating advanced robotic systems for manufacturing and assembly, hence promoting higher levels of productivity, quality, and adaptability in industrial settings.

Article History
Article Received: *25 January 2021*
Revised: *24 February 2021*
Accepted: *15 March 2021*

Keywords: Assembly line, Robotics, intelligent robotics, Robotic Arm

Introduction

Although frequently utilised in automated manufacturing, industrial robotic arms lack the dexterity needed for delicate assembly operations like Ethernet connection assembly. It is difficult to set and programme robot trajectories using conventional approaches for such tasks. Robotic manufacturing has developed a collaborative environment where humans and robots may work together to overcome this. When compared to traditional teach pendants, collaborative robots that have force sensors in their joints may be trained by physically directing their movements. This makes them more user-friendly and versatile. Due to the difficulty of teaching assembly trajectories using

ISSN: 2094-0343
DOI: https://doi.org/10.17762/msea.v70i1.2507
conventional techniques, this method has grown in favour. Teach pendants are difficult to use and useless for teaching these kinds of tasks. In summary, the adoption of collaborative robots with force sensors is a result of the rising demand for sensitive assembly activities.Collaborative robots are becoming more and more common, however their force sensors in the joints frequently miss the tool centre point (TCP) and the contact force applied to objects. Alternative teaching strategies using robotic arms have been created in response. The robot interface developed by Kronander and Billard [5] allows the instructor to modify the stiffness of the robot as it moves. A human motion capture system was used by Shin and Kim [6] to train robot mobility. While [8] created a visual-haptic teleoperation system, Crainic and Preitl [7] presented an ergonomic operating interface employing a game-pad with joysticks. However, when it comes to assembling sensitive components, these methods have their limitations. Some techniques [7], [9], [10] do not capture force trajectories from demonstrators or force feedback data.

This research describes a novel method for teaching assembly tasks quickly via human demonstration that blends machine learning and robot control. The suggested method employs a haptic device with a force sensor mounted at the end-effector of a robotic arm to solve real-world assembly challenges in the industrial setting. During robotic arm operations, operators receive tactile feedback that communicates the contact force between components and the surroundings. The force sensor records arm trajectories and force feedback while the haptic device is used to control the robot end-effector during the teaching process.A trajectory learning system is designed to guarantee the smoothness of teaching trajectories and minimise environmental disturbances that may result from manual haptic device operations. This method enables the creation of the best robotic arm trajectories by allowing users to repeatedly teach and record trajectories and force feedback[14].

The application of force sensing in a haptic device for training, the construction of a trajectory learning system to improve robotic arm trajectories, and the integration of machine learning and robot control for practical assembly jobs are the main contributions of this work. The suggested system intends to improve the effectiveness and adaptability of robotic assembly processes in industrial settings by utilising these developments.

I. Background

1. Learning Environment For Robotic Arm

Using a teach pendant or a human-computer interface (HCI), [21] direct teaching techniques entail physically moving the robotic arm. Robot motions are manually directed by operators, who record the trajectories for later replay. The motions of the robot can be directly controlled by the user via teach pendants, which are portable devices having buttons, joysticks, and touchscreens. On the other hand, HCIs offer a graphical user interface (GUI) that enables users to communicate with the robot and set up its commands.On the other hand, indirect teaching techniques entail programming the robot's actions using complex commands or programming languages. These procedures usually involve less direct manipulation of the robot and are more abstract. Instead, operators instruct the robot to interpret and carry out the desired actions, sequences, or tasks. Programming by demonstration, wherein operators direct the robot through the desired motions while the system records and learns the actions, and offline programming, wherein operators define the robot's

ISSN: 2094-0343
DOI: https://doi.org/10.17762/msea.v70i1.2507

actions using specialised software without having to interact with the robot directly, are two examples of indirect teaching techniques.

For the purpose of training robotic arms, both direct and indirect teaching techniques are essential. While indirect methods allow for more advanced programming and automation, direct methods offer real-time control and fine-tuning capabilities. The particular application requirements, task complexity, operator preferences, and level of experience all influence the selection of the instructional methodology.

2. Systems For Trajectory Learning

Datasets for trajectory and force feedback [22] are produced after the teaching procedure. However, because human demonstrations are subject to vibrations and mistakes, the robotic arm may follow less-than-ideal trajectories. As a result, before using the instructional data in actual processes, it must be optimised and learned.A hidden Markov model (HMM) is used to find trajectory features in order to remedy this. On the basis of the instructional dataset, the[15] trajectory prediction model was created using the HMM. However, due to the nature of the HMM, a small number of states can result in inefficient trajectory learning, whereas a high number of states can slow down calculations.In contrast, [16] used Gaussian mixture regression (GMR) to examine the features of the instructional dataset and incorporate them into a trajectory. Important trajectory features are kept during trajectory learning by adding GMR. This study uses GMR to speed up robotic arm trajectory learning without losing the key elements of demonstration teaching data. Units of analysis are the data points along the trajectories.

For robotic arms, controllers are frequently employed in conjunction with force sensors to reduce environmental disturbances. Popular options include PID (Proportional-Integral-Derivative) and compliance controllers [18]. The majority of external disturbances, however, are nonlinear, necessitating a variety of control reactions to adequately address varied situations. In contrast to neural networks (NNs), which allow for direct formulation of control models using training data, fuzzy control is frequently used in robotic arm control. Fuzzy control and NNs work together to create complex fuzzy control rule databases that are based on NNs, combining the benefits of both approaches. Robotic arm movement models have been trained using adaptive neuro-fuzzy inference systems (ANFIS), which have been used to overcome the inaccurate mathematical dynamic function inference brought on by persistent external disturbances.Compliance control can be passive or active, both of which require adjusting to external disturbances through contact with force feedback. While active compliance control makes use of controllers for more robustness, passive compliance control uses hardware components to react to outside stimuli. Extensive research has been done on compliance control techniques including hybrid motion control and impedance control. The problems associated with contact force have been addressed via hybrid impedance control[9].

3. Systems For Educating, Learning From Trajectories, And Controlling

For this system to produce a collection of taught trajectories and force feedback data, various teaching processes had to be used. It was a force sensor and haptic device attached to the robotic arm's end. The force feedback data recorded by the force sensor was used to give the operator tactile feedback via the haptic device. This input improved the system's intuitiveness and usability

ISSN: 2094-0343
DOI: https://doi.org/10.17762/msea.v70i1.2507

by removing vibration disruptions, weight inaccuracies, and coordinate transformations during the teaching process. After the teaching procedure, the data obtained for this work was represented with regard to the robot's base coordinate system. The system's various functions were each highlighted individually, emphasising their individual roles and functionalities.

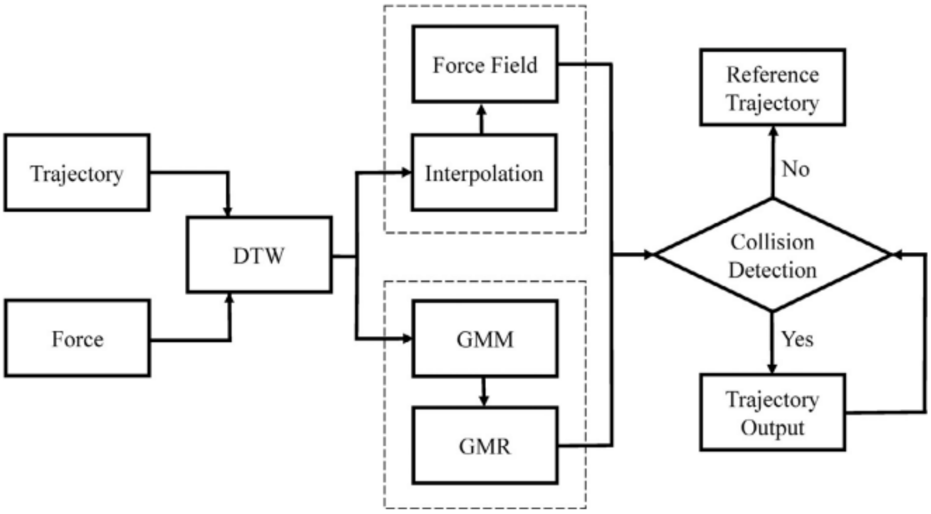


Figure 1: Learning System for Trajectory learning mechanism

The system enabled the extension of the scale, allowing the control of the robotic arm to do large-scale actions through small-scale motions of the haptic device, to produce a rough trajectory. On the other hand, the size might be reduced for exact trajectories, making precise arm movements possible. Therefore, a scaling parameter has to be multiplied by the relative position of the haptic device (H Hold -). This scaling parameter allowed the haptic device's movements to be scaled to the appropriate degree of control and accuracy for the robotic arm.

The system was created specifically to repeatedly process the force feedback and trajectory data from the training system. The control system would use the reference trajectory and the related predicted force that were produced through this iterative process to execute the motion. The dynamic time warping (DTW) technique was used to align the dynamic time of all teaching data in order to maintain time consistency.By preserving the key curve characteristics of the trajectories, Gaussian Mixture Regression (GMR) was used to determine the best reference trajectories and predicted force. In order to ensure the safety of the reference trajectories during execution, a three-dimensional force field was also created to simulate them. Figure 1 shows a diagram displaying the trajectory learning system.

4. (Smmd-Dtw) Slide Multiple Multi-Dimensional Time Warping

The generated instructional data had a variety of trajectories when the teaching procedure was finished. Each element of the trajectory teaching process took a different amount of time to complete because of the manual labour and repetitions necessary. Therefore, Dynamic Time Warping (DTW) is required for the instructional data.The purpose of conventional DTW techniques is to handle a single set of input data in a single dimension. The taught trajectories in this work have numerous dimensions and datasets, therefore a more effective strategy is needed to shorten the calculation time. A method known as Slide Multiple Multidimensional Dynamic Time Warping

ISSN: 2094-0343
DOI: https://doi.org/10.17762/msea.v70i1.2507

(SMMD-DTW) was suggested [20] to address this.The input data is divided into several segments by SMMD-DTW, which then executes multidimensional DTW. The calculation time is decreased by segmenting the data, enabling more effective processing of multidimensional trajectories. Through the alignment of trajectories in several dimensions, this method makes it easier to compare and analyse the instructional data.

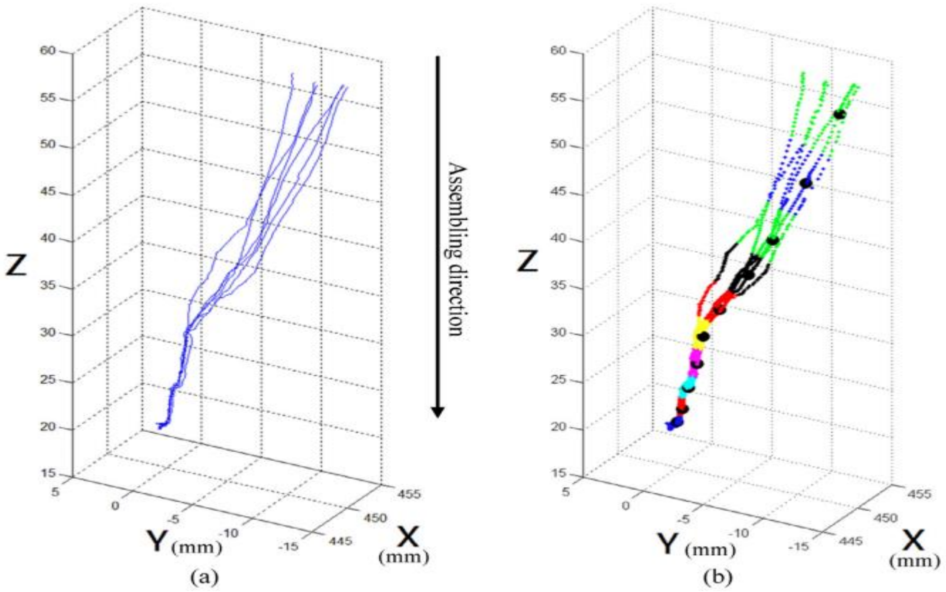


Figure 2: Slide Multiple Multi-Dimensional Time Warping (a) Original Input (b) After SMMDTW

The K-means clustering technique was used to segment the data. Six initial trajectories are displayed in Figure 2(a) to represent various activities. The outcomes of employing SMMD-DTW are shown in Figure 2(b). The same cluster contains all of the phases of the taught acts, each of which is represented by a trajectory of the same colour.The time discrepancies in each phase resulting from variations in operation speed for timeline adjustment in the DTW process are made clear by using K-means clustering and SMMD-DTW. The analysis and comprehension of the changes in completion times for the various phases of the taught acts are aided by this segmentation and grouping approach.

5. Gaussian Mixture Regression (Gmr)

Gaussian Mixture Regression (GMR) was used to generate the ideal reference trajectories and predicted force while keeping the crucial curve features after applying DTW to synchronise the timelines of all the teaching data. GMR's input data may include data from numerous dimensions. One of these dimensions is referred to as the continuous time domain, and the other dimensions are called space domains. The relative chronological relationship between the several space domains is represented by the time domain.The timeline is divided into several continuous points using GMR, and the central point and covariance matrix are produced for each segmentation point using the associated GMM (Gaussian Mixture Model) parameters. The final reference trajectory is created by connecting these core spots.

The K number of Gaussian component segments, abbreviated as GMR, is predefined. This specifies how many points there are in the reference trajectory. Let t stand for the segmentation point on the continuous timeline, and let s stand for the space domain that corresponds to it as determined by

ISSN: 2094-0343
DOI: https://doi.org/10.17762/msea.v70i1.2507
GMR. The GMR parameters and can be represented as follows because the GMR model separates the time and space domains:

$$\mu = [\mu^1, \mu^2, \ldots, \mu_K] \quad (1)$$

$$\Sigma = [\Sigma^1, \Sigma^2, \ldots, \Sigma_K] \quad (2)$$

The mean vector and covariance matrix, μ and Σ respectively, are represented by and in these equations. The subscripts 1 to K represent various Gaussian segments or components.

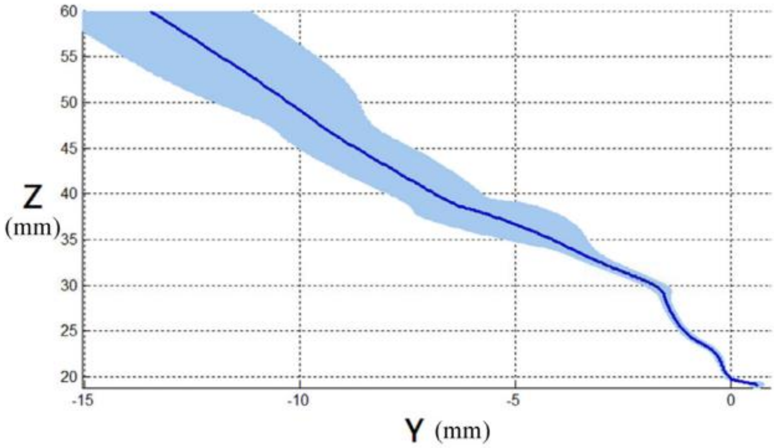


Figure 3: Gaussian Mixture Regression (GMR) result representation

The reference trajectory obtained using GMR is shown in Figure 3. It is produced using 12 navy blue-marked Gaussian components. Additionally, each time segmentation point's covariance level is displayed and is indicated by light blue markers.The segmentation points show a greater degree of convergence as they get closer to the Ethernet connector (Z 25 mm), as seen in Figure 3. This suggests that the trajectory becomes less variable and more constant there, indicating a more steady and reliable motion pattern close to the Ethernet connector.

II. Controlling System

The system structure developed for this study's final component was designed to accomplish instant control of the robotic arm and guarantee secure operations even in the event of outside disturbances or fixture displacement while following the reference trajectory. The arm was controlled by observing and making use of the discrepancies between the present force feedback values and the expected force in this control system, which was based on admittance control principles [12].Additionally, the controlling system used force feedback to continuously assess the many kinds of environmental disturbances. Based on this evaluation, it swiftly changed the entry weight, enabling the system to quickly alter and efficiently react to changing external circumstances. The robotic arm was able to retain stability and improve operational performance thanks to this dynamic modification of the entry weight.

1. Control of admission

The main goal of the controller was to produce the intended or anticipated force, which the trajectory learning system created simultaneously with the reference trajectory. The following equation represents the admittance control of the trajectory's X-axis:

$$F_{desired} = K_{adm} * (X_{desired} - X_{current}) + F_{expected} \quad (3)$$

ISSN: 2094-0343
DOI: https://doi.org/10.17762/msea.v70i1.2507

F_expected is the anticipated force derived by the trajectory learning system, K_adm is the admittance gain or weight, X_desired and X_current are the desired and current positions of the robotic arm along the X-axis, respectively, and K_adm is the admittance gain or weight in this equation. The intended force needed to drive the robotic arm along the X-axis is generated by the admittance control algorithm using the difference between the desired and actual positions as well as the expected force.

$$F\_desired = F\_current + K\_x * (\Delta X - \Delta X\_old) + D\_x * \Delta X\_dot \qquad (4)$$

- F_current represents the current force feedback value (N).
- ΔX represents the translation of the robotic arm in the X direction (m).
- ΔX_dot represents the change in the speed of the arm in the X direction (m/s).
- K_x represents the stiffness in the X direction (N/m), indicating the relationship between stress and force feedback.
- D_x represents the damping coefficient of the X-axis (Ns/m), indicating the relationship between speed and force feedback.
- ΔX is calculated as the difference between the current position X_old and the position at the next time point X_new.
- ΔX_dot is calculated as the change in speed from the previous time point X_dot_old to the subsequent time point X_dot_new.
- Δt represents the change in time.

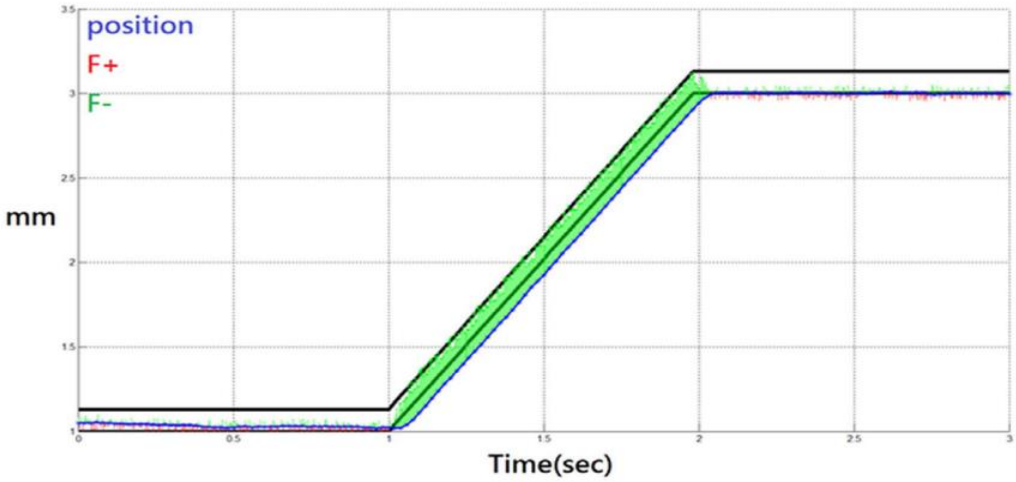


Figure 5: Robotic arm executing the translation through the simulation's admission control

2. Evaluating the admissions situation

The following method was used to assess if the current disturbance is due to vibration or simple translation and to calculate the vibration's amplitude. The predicted force, F_exp, was established as a broad band range, designated as B. Based on the mean of the continuous force feedback values, the present state of the force feedback, indicated as S, was established. It was also taken into account how many changes, H (zero crossing rate, ZCR), there were throughout the states.

The force feedback state, S, was classified into three types:

- Positive state: When the mean of the current continuous force feedback values was larger than F_B+ (upper bound of the range B), S was considered positive.

- Negative state: When the mean was smaller than F_B- (lower bound of the range B), S was considered negative.
- Middle state: When the mean was within the range of B, S was considered middle.

It was possible to identify changes in the force feedback behaviour by contrasting the current state with the previous state. This method made it possible to discern between vibration and translational disturbances and to calculate the vibration's amplitude. Additionally, the robotic arm's operation was stopped for safety reasons if the vibration amplitude was too high.

III. Result and Discussion

The experiment's goal was to use a robotic arm control system to complete an assembly task while employing a reference trajectory learned from teaching and trajectory learning systems. During the assembling process, it was intended to lessen force feedback while still producing the desired force. An Ethernet connection [20] was used as the component in the experiment.As seen in Figure 6, the Ethernet connector was made up of a black plastic component and an aluminium shell with a latch. The aluminium shell, which was firmly set in a fixture before the experiment, was grasped by the robotic arm utilising the training system, and it was inserted into the aluminium component.

a) Demonstrating and Learning the assembly procedures

The teaching system was used to control the robotic arm while it carried out the component assembly procedure six times using the coordinate system. There were variances in the finished actions because the training procedure was carried out manually for each assembly step. As a result, the instructional data were subjected to many iterations of the trajectory learning process.The SMMD-DTW algorithm was used in the trajectory learning phase, with a cluster size of 10. The GMR trajectory learning procedure used 12 Gaussian components and the instruction data to produce the reference trajectory and anticipated force for the robotic arm to use.Figure 6(b) depicts the anticipated force generated following the six teaching processes, while Figure 6(a) displays the contact force generated throughout the six teaching processes.

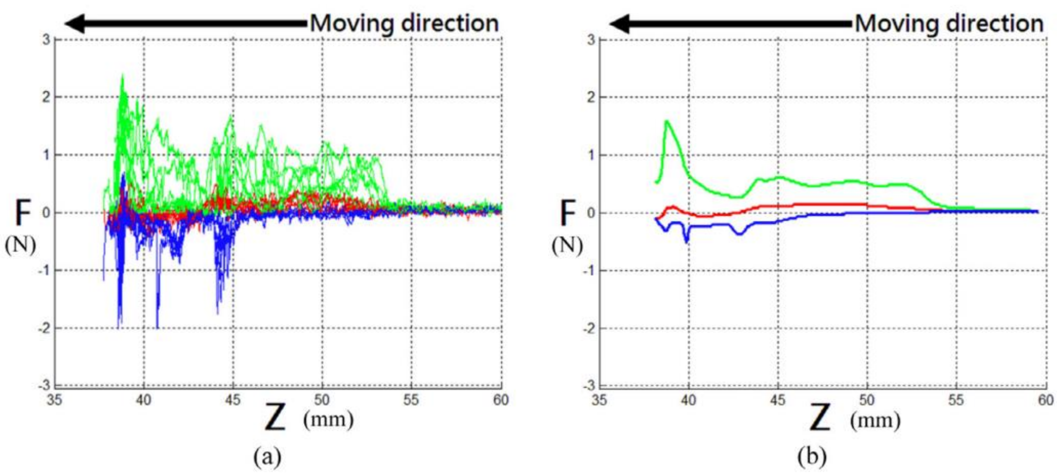


Figure 6: Schematic Representation (a) Force feedback that was taught (b) force that was anticipated after learning.

ISSN: 2094-0343
DOI: https://doi.org/10.17762/msea.v70i1.2507

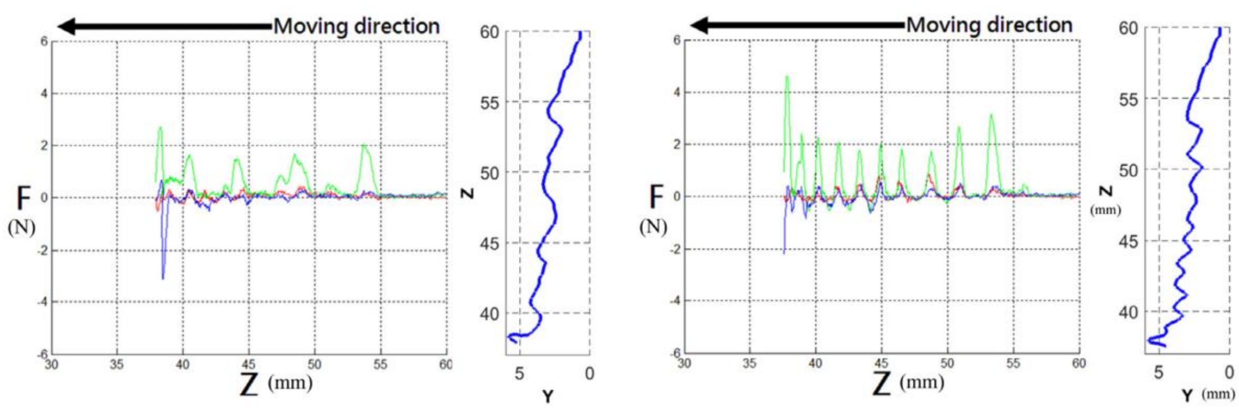
The average values of FX, FY, and FZ from four trials carried out at various vibration frequencies are shown in Table 1. Due to the installation of admittance control, the average FY values remained consistent despite the existence of disturbances along the Y direction.

Table1: Vibration frequency analysis

Frequency	Ave. FX	Ave. FY	Ave. FZ
0.5 Hz	0.053275	0.48565	-0.054575
1.0 Hz	0.064925	0.50575	-0.04395
1.5 Hz	0.052925	0.492675	-0.032875

b) Vibration assembly

Vibration assembly tests were carried out to evaluate the controller's responsiveness within the regulated range of vibration frequencies. No translation of the aluminium shell (Shift = 0) took place in these trials prior to the vibration phase. Based on the force input acquired during the vibration, the trajectory was calibrated.The finished product, an Ethernet connector, was made out of parts with minute gaps. The assembly process's 1 mm maximum acceptable error was established. If this mistake level was crossed, the excessive force feedback that followed would cause the system to automatically stop the assembly action. As a result, 1 mm was chosen as the experiment's vibration amplitude.



(a) (b)

Figure 7: following admittance control (a) at frequency 0.5 Hz (b) frequency 1.5Hz

The experiment's vibration frequency was kept below 2 Hz, and the admittance weight (Rc) was adjusted to 1. The force feedback data captured at vibration frequencies of 0.5 Hz and 1.5 Hz, respectively, are shown in Figures 7(a) and (b). The robotic arm underwent a noteworthy peak in stress as a result of the vibration's magnitude in the Y direction. The robotic arm's trajectory was tracked, and the findings are presented in Figure 7. This figure shows how the arm's trajectory significantly changed in reaction to the vibrations of the environment.

IV. Conclusion

In order to increase productivity, efficiency, and safety in a variety of industrial applications, improved robotic system design and control are essential. Assembly processes can be made exact and reliable by combining teaching systems, trajectory learning, and cutting-edge control algorithms like admittance control.By utilising teaching systems, complex assembly jobs can be carried out by the robotic arm with less force feedback and greater precision. This is done by capturing and optimising reference trajectories. The performance of the robotic system is further improved by trajectory learning techniques like SMMD-DTW and GMR, which contribute to the production of ideal reference trajectories and predicted forces.Admittance-based control is used to ensure adaptation to environmental changes and outside disturbances throughout the assembly process. The system can dynamically respond to changing conditions and maintain stable and secure operations by continuously monitoring force feedback and modifying the admission weight.The installation of an Ethernet connector serves as an example of experimental results that indicate how effective the suggested strategy is. The robotic system successfully manages vibrations, precisely detects trajectories, and generates the appropriate force levels, resulting in successful and dependable assembly results.There is a lot of potential for enhancing automated processes, lowering the need for human labour, and raising overall productivity and quality in a variety of industries through the design and control of advanced robotic systems for production and assembly. The potential for improving manufacturing and assembly capabilities in this area is promising and warrants more research and development.

References:

[1] A. Mohammed, B. Schmidt, L. Wang, Active collision avoidance for human-robot collaboration driven by vision sensors, Int. J. Comput. Integr. Manuf. 30 (9) (2017) 970–980.

[2] J. O. Oyekan, W. Hutabarat, A. Tiwari, R. Grech, M. H. Aung, M. P. Mariani, L. López-Dávalos, T. Ricaud, S. Singh, C. Dupuis, The effectiveness of virtual environments in developing collaborative strategies between industrial robots and humans, Rob. Comput. Integr. Manuf., 2019, 55, 41–54.

[3] C. Bernier, Collaborative robot series: Kuka's light weight robot 4+, Availabe athttp://blog.robotiq.com/bid/64944/Collaborative-Robot-Series-KUKA-s-LightWeight-Robot-4(2017/2/16).

[4] A. Cherubini, R. Passama, A. Crosnier, A. Lasnier, P. Fraisse, Collaborative manufacturing with physical human-robot interaction, Rob. Comput. Integr. Manuf. 40 (2016) 1–13.

[5] K. Kronander, A. Billard, Learning compliant manipulation through kinesthetic and tactile human-robot interaction, IEEE Trans. Haptics 7 (3) (2014) 367–380.

[6] S.Y. Shin, C. Kim, Human-like motion generation and control for humanoid's dual arm object manipulation, IEEE Trans. Ind. Electron. 62 (4) (2015) 2265–2276.

[7] M.-F. Crainic, S. Preitl, Ergonomic operating mode for a robot arm using a gamepad with two joysticks, IEEE Int. Conf. Applied Comput. Intell. and Inform, (2015), pp. 167–170.

[8] X. Xu, A. Song, D. Ni, H. Li, P. Xiong, C. Zhu, Visual-haptic aid teleoperation based on 3-denvironment modeling and updating, IEEE Trans. Ind. Electron 63 (10) (2016) 6419–6428. 2016

[9] H.I. Lin, C.L. Chen, A hybrid control policy of robot arm motion for assistive robots, IEEE Int. Conf. Inform. and Automat. (2011), pp. 163–168.
[10] J. Aleotti, A. Skoglund, T. Duckett, Position teaching of a robot arm by demonstration with a wearable input device, Int. Conf. Intell. Manipulation and Grasp. (2004).
[11] P.K. Artemiadis, K.J. Kyriakopoulos, EMG-based control of a robot arm using lowdimensional embeddings, IEEE Trans. Rob. 26 (2) (2010) 393–398.
[12] J. Rossmann, C. Schlette, N. Wantia, Virtual reality in the loop-providing an interface for an intelligent rule learning and planning system, Workshop Semantics Identification Control Robot Human Environ, IEEE Int. Conf. Robot. Automat. (2013), pp. 60–66.
[13] F. Kobayashi, K. Hasegawa, H. Nakamoto, F. Kojima, Motion capture with inertial measurement units for hand/arm robot teleoperation, Int. J. Appl. Electromagnet. Mech. 45 (1–4) (2013) 931–937.
[14] D.A. Duque, F.A. Prieto, J.G. Hoyos, Trajectory generation for robotic assembly operations using learning by demonstration, Rob. Comput. Integr. Manuf. 57 (2019) 292–302.
[15] S. Qiao, D. Shen, X. Wang, N. Han, W. Zhu, A self-adaptive parameter selection trajectory prediction approach via hidden Markov models, IEEE Trans. Intell. Transp. Syst. 16 (1) (2015) 284–296.
[16] S. Calinon, F. Guenter, A. Billard, On learning, representing, and generalizing a task in a humanoid robot, IEEE Trans. System. Man Cybern. Part B 37 (2) (2007) 286–298.
[17] A. Cohn, Z. Ghahramani, M.I. Jordan, Active learning with statistical models, J. Artif. Intell. Res. 4 (1996) 129–145.
[18] W. Yu, R.C. Rodriguez, X. Li, Neural PID admittance control of a robot, Am. Control Conf. (2013), pp. 4963–4968.
[19] C. Ott, A. Dietrich, A. Albu-Schäffera, Prioritized multi-task compliance control of redundant manipulators, Automatica 53 (2015) 416–423.
[20] R. Sharma, V. Kumar, P. Gaur, A.P. Mittal, An adaptive PID like controller using mix locally recurrent neural network for robotic manipulator with variable payload, ISA Trans. 62 (2016) 258–267.
[21] K.V. Lakshmi, M.u. Nabi, An adaptive neuro-fuzzy control approach for motion control of a robot arm, Int. Conf. Inform., Electron. & Vision, (2012), pp. 832–836.
[22] T. Nozaki, T. Mizoguchi, K. Ohnishi, Decoupling strategy for position and force control based on modal space disturbance observer, IEEE Trans. Ind. Electron 61 (2) (2014) 1022–1032