DIGITAL SHADOW MODEL FOR AUTOMATED CABIN ASSEMBLY PROCESS

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Abstract

Digital transformation of the shop floor focuses not only to automate the process, but also to collect and transform the process data, with which effective data analytics is feasible. Due to the advanced communication technologies and decreasing cost for data storage, the amount of data generated on shop-floors is increasing rapidly on a daily basis. Using the metadata from the shop-floor, process-improvement based on the feedback is possible with modern data analytics. Real time information from the physical system is collected and stored, from which record-and-replay of the stored information on cabin assembly process is realized. With this motivation of record-replay of events along with remote monitoring of live data, the purpose of this paper is to introduce a digital shadow model for automated cabin assembly process.

1. INTRODUCTION

Modern technologies accelerate the conventional manufacturing processes, where digitalization of the process results in higher productivity. Digitalization in the Industry 4.0 domain allows easy integration of interconnected components on the shop-floor. As a technological basis of Industry 4.0, it is proposed to embed electronics, software, sensors and more importantly to implement the network connectivity between devices for enabling the data collection and exchange via the internet [1]. This results in physical systems being connected to the virtual world, where the stored data can be utilized for virtual operations. Consequence the performance analysis of executed operations can be made in virtual world while also deducing critical parameters of the physical operations. Using the advanced technologies, it is possible to monitor the process in real-time and to link the physical world activities to virtual world where real-time data should be properly modeled to enable the intelligent decision making.

The digital twin can be seen as the virtual and computerized analogue of the real-time physical system that can be used to simulate the behavior of physical system in various ways, capitalizing on the real-time synchronization of the data originating from different field sensors [1]. In contrast, a digital shadow provides sufficient, content-related picture of the process with a unidirectional information flow from physical to digital world. In line with other activities at the German Aerospace Center (DLR) to implement a digital thread for the whole cabin assembly process, the digital shadow is generated based on the feedback information from the automated assembly process. Ontology plays central role in assembly-planning to describe the sequence of events. Robots are utilized for enacting the commands that ontology describe and sensors are deployed to assist the robots by identifying objects and obstacles. The feedback data from robots, sensors and other actuators during the autonomous assembly process constitutes the process metadata and it is stored in HDF5[1] format for further analysis and validation. The representation of the stored data in virtual world is achieved by the digital shadow model generated using open source software such as Blender.

The paper is structured in following manner: Section 2 describes the state of art related to digital shadow, section 3 provides hardware for the digital shadow and section 4 describes the measures and interpreting sensors data followed by relating parameters for cabin assembly in section 5. Section 6 elucidates the replaying of stored data for visual analysis and section 7 provides the conclusion and future work.

2. STATE OF ART

Industrial process improvement based on feedback information has been researched for quite some time. Besides providing a deeper understanding on different proposed definitions of digital twin, the objective of *Negri et.al* [1] is to help in identifying the role of digital twin for manufacturing w.r.to Industry 4.0 and it gives the background information on implementation of digital twin in different areas of manufacturing. *Thomas Bauernhansl et. al* [2] show a roadmap for digital shadow model for production, where different stages of development are mapped to their complexity level in matrix form. It is also mentioned that using meta information about the stored data and by analyzing the semantics of the stored information, digital shadow would be able to cleanup data redundancies, compression tasks etc. *Ehrdahrt et. al* [3] present a model for operational optimization in manufacturing environment using digital shadow. In addition, the idea of using digital shadow for predictive analytics is presented, in order to support the understanding of process anomalies through data from live visualization. Based on the data from digital shadow, information for optimization problem is derived from five fundamental parameters: 1. time, 2. position, 3. stock, 4. status, and 5. product derivative. The amount of recorded data is reduced by using event-based recording. The fundamental parameters are linked to the critical parameters such as 1. Cycle-time 2. Utilization of single systems, 3. Delivery reliability 4. The number of products in circulation. Data from digital shadow are segregated into fragments and local optimum is found using genetic

[1] Hierarchical Data Format

algorithm and it is introduced "bottleneck-oriented hypothesis" to find global optimum. *Uhlemann et. al.* [4] demonstrates the learning factory to showcase the benefits of employing digital twin for production systems. In order to illustrate the vital differences between digital twin and conventional way of value stream mapping to the participants of the learning factory, the important concepts of digital twin viz., data acquisition, data warehousing and data analysis are exemplified with scenarios for better understanding.

The digital shadow as a function is introduced in [5], where time is mapped to two dimensions: tree structure corresponding to the structure of physical object and an attribute vector for each object. With the tree structure, parent-child relation between different participating departments (of manufacturing) is established, thereby a whole factory can be represented and could be mapped to digital shadow. Any activities like assembly process that causes physical movements denotes the change in node parameters. Appropriate data storage mechanism is also described, where a dedicated data-base for the digital shadow is defined in addition to a data base for continuous data.

Digital shadow is described as a platform to integrate information from different sources such that the miscellaneous real-time analysis is enabled to make right decisions [6]. A real time application is shown where the hot rolling process is taken into consideration for digital shadow, since it is highly energy consuming process, where process improvements will directly affect the carbon footprint. Hot rolling comprises of five stages: 1. Casting 2. Heating 3. Rolling 4. Stamping 5. Service life. Scheduling the process based on FEM analysis normally takes 30 minutes - 4 hours. Complex mathematical models based on different process parameters influencing the slab dimensions, its microstructure, thermal condition and process' energy impact are evaluated. Model based digital shadow is generated based on the generated models that reduced the evaluation time from 30-240minutes (FEM[2] based) to 50ms.

This paper focuses on developing a digital shadow model for the autonomous cabin assembly process, where the feedback information from the physical model is used for analysis and to aid the live visualization to enable the intelligent decision making.

3. HARDWARE INFRASTRUCTURE FOR DIGITAL SHADOW

At the DLR, autonomous cabin assembly process is researched using a pre-assembly cell along with robots, sensors and other controls. Two robots are installed on the pre-assembly cell, which performs assembly operations on components, thereby building a subassembly of the cabin. Sensors, including cameras assist the motion of robots. Detailed information about the assembly infrastructure is provided by [9].

Understanding, evaluating and improving the existing process based on feedback data is considered to be the primary objective of the digital shadow of cabin assembly. The main pillars of digital twin model are: 1. Data acquisition, 2. Data storage and 3. Data analysis. Here the information about the respective hardware is elucidated.

1. Data acquisition

The pre-assembly cell is equipped with central PLC[3] system, that communicates with robots on the cell along with the capability to be interfaced with different external sensors such as vibration sensor, noise sensors etc. using the appropriate function modules. OPC UA[4] communication is enabled in the PLC such that PLC acts as an OPC UA server, and any hardware connected for data acquisition can be OPC UA client. This is shown in figure 1.

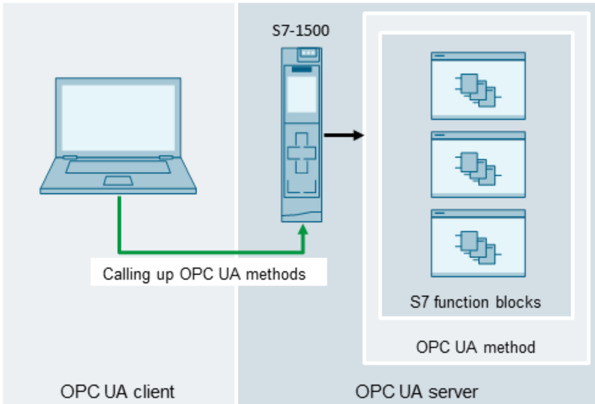

Figure 1: OPC UA communication in Siemens TIA Portal[5]

Since OPC UA is open-source and being used as global communication standard, hardware-independent communication is implemented. Hardware implementation is not in scope of this research, so more details on data acquisition is not presented here. However, it must be stated that it is important to record the context information as part of feedback data, so that the data analysis made on the stored information fetches the cross interpretation of external disturbances with the robot parameters.

2. Data storage

This work leverages the use of HDF5[6] format for storing the feedback information from the different hardware from pre-assembly cell. It is an open-source file format that supports large, complex, heterogenous data[7]. HDF5 format stores the data in binary format such that larger information can be stored in a file with relatively smaller file-size. Data from robots and external sensor data along with context information (as in figure 2) are stored in HDF5 which is later used for analysis. For picking a side-wall panel from storage and placing the panel on the pre-assembly cell, the associated context could be "pick sidewall panel" and "place sidewall panel". The role of contextual information is very much beneficial for visualization and visual inspection. The third pillar of digital model i.e., Data analysis is

[2] Finite Element Method
[3] Programmable Logic Control
[4] Open Platform Communications Unified Architecture
[5] https://support.industry.siemens.com/cs/document/109756885
[6] Hierarchical Data Format
[7] https://www.neonscience.org/resources/learning-hub/tutorials/about-hdf5

explained in next section.

Timestamp	Joint1 position	Joint2 position	Joint3 position	Joint4 position	Joint5 position	Joint6 position	Context information
1626777644	180.09	56.51	78.76	90.09	124.54	10.08	Pick sidewall panel
1626777645	178.54	57.24	77.23	90.08	125.17	10.24	Pick sidewall panel
1626777646	178.18	58.12	76.98	90.08	125.76	10.09	Pick sidewall panel
1626777647	173.21	59.37	76.17	90.07	126.38	10.13	Pick sidewall panel
1626777648	174.16	59.89	75.86	90.06	126.96	10.54	Pick sidewall panel
1626777649	171.87	60.23	75.03	90.09	127.85	10.26	Pick sidewall panel
1626777650	170.23	61.09	74.34	90.09	128.11	10.34	Pick sidewall panel
1626777651	169.87	61.67	73.98	90.09	129.27	10.13	Pick sidewall panel
1626777652	168.97	62.09	72.78	90.09	130.03	10.09	Pick sidewall panel
1626777653	168.16	63.13	72.65	90.09	131.98	10.25	Pick sidewall panel
1626777654	166.51	64.45	71.89	90.08	132.21	10.01	Pick sidewall panel
1626777655	182.12	64.98	71.89	90.08	132.36	10.39	Pick sidewall panel
1626777656	181.97	65.10	71.89	90.07	132.94	10.03	Pick sidewall panel
1626777657	181.24	65.97	71.89	90.05	133.08	10.05	Pick sidewall panel
1626777658	180.98	65.87	71.89	90.07	133.09	10.09	Pick sidewall panel

Figure 2: Joint position data with contextual information

4. PROCESS METADATA FOR DIGITAL SHADOW

Data from the different hardware in the pre-assembly cell constitutes to the process metadata. This data is later analyzed for any process improvements. The automated pick-and-place operation with robot is exemplified in figure 3 and the corresponding sensor-data is shown in figure 4. For autonomous pick-and-place operation, sensors assist the process-planning to ascertain if the objective of pick-and-place operation is successful. Digital shadow of the process collects the information from different sensors that could be used for analyzing the process parameters. Based on mathematical computation of different parameters, process improvement is envisioned.

As depicted in figure 4, there are different sensors information available for the pick-and-place operations. At top level, they are classified into 1. Internal robot sensors 2. External environmental sensors. Some of the robot data, such as joint position, velocity could be directly used by the controller for necessary motion whereas other information is not necessarily used by controller (data in dotted round circles). Similarly, in environmental sensors information from cameras are directly inferenced for successful object pick and place operation.

Information from aforementioned sensors together with other sensors contribute the feedback data of the pre-assembly cell. The information from sensors such as temperature, current, vibration etc. are used for evaluating the effectiveness of process and to improve it. This is explained in following sections.

4.1 ANALYZING PROCESS METADATA

In this section the important parameters to evaluate robot performance are discussed, along with the importance of interpreting such information for process improvement measures. Analyzing metadata from the entire will not only improve process time, but also aids in avoiding future errors. This section explains the measures to enhance the process execution utilizing the feedback data along with the different parameters to analyze. There are two topics addressed here:

1. Indicators to measure robot performances

2. Improving robot performance using sensors data

4.1.1 INDICATORS TO MEASURE ROBOT PERFORMANCE

The ontology for the cabin assembly process schedules and assigns different robots based on process time [7]. This is shown in figure 5,

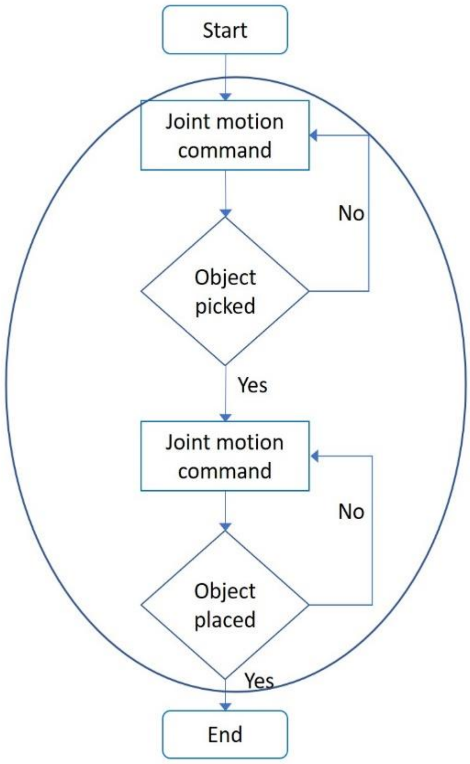

Figure 3: Flow diagram of autonomous pick-place operation

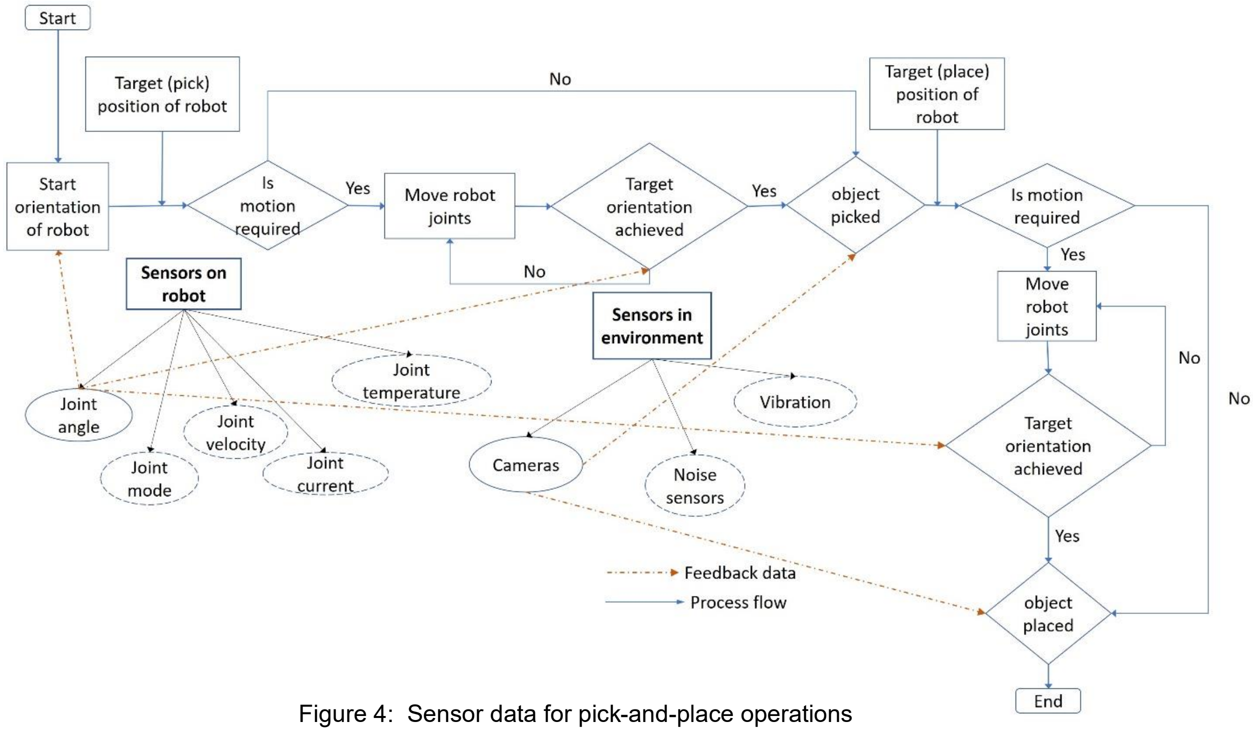

Figure 4: Sensor data for pick-and-place operations

where the APAS[8] robot is chosen based on the process execution time and the process sequence is generated by ontology. In this paper the performance evaluation is described, which aren't directly part of the ontology w.r.to process planning. There are different parameters to measure in order to understand the performance of the robot, which directly or indirectly influence the process execution time [8].

1. Resolution

The resolution describes the smallest increment that the robot is able to move. This is determined by the robot controller. In the scope of the autonomous cabin assembly process, resolution describes the robot's ability to move on a single instruction from one timestep to next timestep.

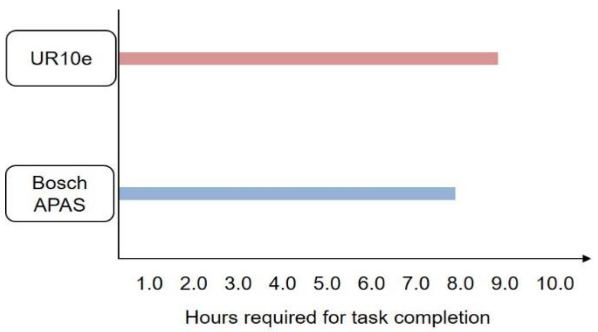

Figure 5: Process planning based on process execution time

2. Accuracy

It describes the ability of the robot to reach the desired target position/orientation. For a pick-and-place task of the robot, accuracy error denotes the spatial distance between the expected location to pick/place and the actual location the robot actually places the end-effector to pick/place. expected location to pick/place and the actual location the robot actually places the end-effector to pick/place.

$$\boldsymbol{Accuracy\ error = Actual\ position\ of\ ee - Desired\ position\ of\ ee}$$

ee: End effector of the robot

3. Precision

Precision measures the ability of the robot to reach a

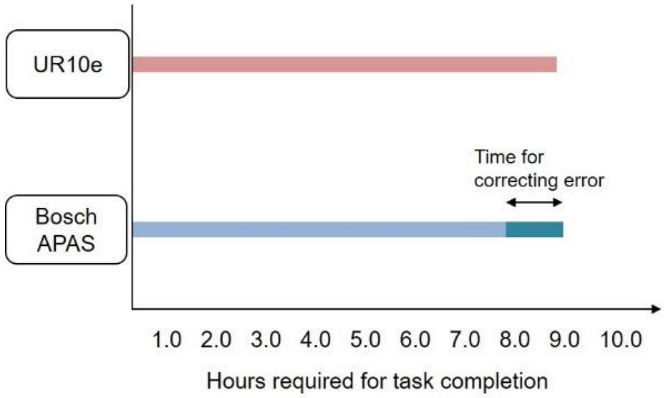

Figure 6: Prolonged process execution time

particular position repeatedly over a period of time. While accuracy measures the deviation from target, precision measures the ability to repeat the motion resulting in same position. For a picking operation, accuracy could identify the number of successful attempts in picking objects over a period of time while precision will denote the number of successful attempts of the robot to pick different objects at same location over a period of time. Errors in precision and

[8] APAS – Automatic Production Assistants

accuracy lead to position errors of the desired object on the pre-assembly cell. Any disturbance in the parameters described above will influence the process execution time as shown in figure 6.

4.1.2 SENSOR DATA FOR PROCESS IMPROVEMENT

Previous subsection elucidated the measures of robot performances, while in this subsection the plausibility of using sensor information for the digital shadow model is discussed. Different pieces of robot-based sensor information such as position, orientation, current etc. are available. Theoretically, information from these sensors should suffice to comprehend the performance measurements of robot for any desired task. But in real time, there are more disturbances such as effects of vibrations, objects position relative to robot, type of handled object (such as metal or non-metal) etc. which must be considered.

INTERPRETING SENSORS DATA

Different disturbances can contribute to problems during the execution of intended task. For example, induced vibration could result in positional disturbances such that the operation of picking an object by the robot would take more time until the vibration reduces or the robot controller was able to negotiate the induced vibration. The positional distortion of an object with induced vibration may look as in figure 7.

The velocity of the robot joints can directly influence the accuracy and precision of the robot [8] and is shown in figure 8. In addition, the applied payload plays crucial role in achieving the desired results. Similarly, the different individual disturbances (such as joint current, joint voltage, noise) might cause the problems with robot tasks, and their behavior and can have influence on the robot performances. The expected outcome of such interpretations is detailed in next section, which elucidates the results of the interpretations in detail. The following section describes the methodology of digital shadow model and the purpose of using it in cabin assembly and expected results.

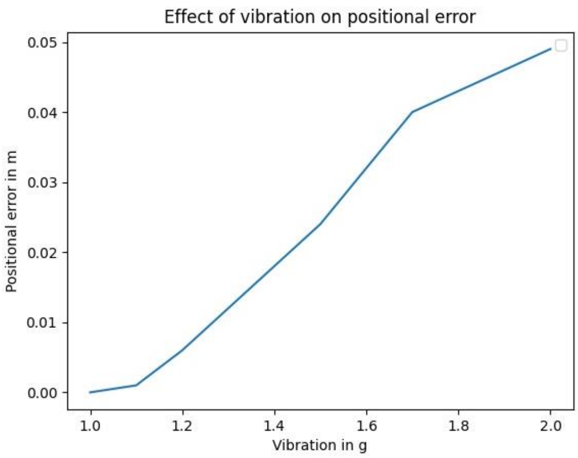

Figure 7: Vibration vs positional error

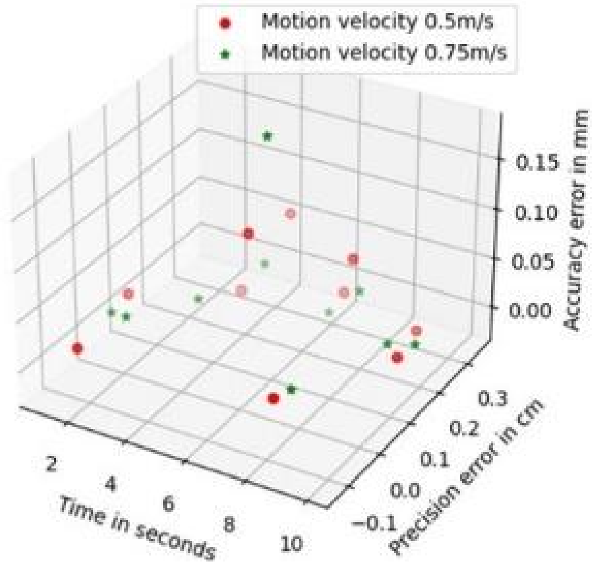

Figure 8: Effect of velocity on precision and accuracy

5. UNDERSTANDING ROBOT PERFORMANCE FOR AUTOMATED CABIN ASSEMBLY

The important part of this paper is the data analysis of the digital shadow for process improvement. As described in the previous section, an understanding of the effect of different disturbances on robot performance is required for effective process analysis and improvement. The disturbances induce the error in positioning of the end-effector at desired location as shown in figure 9 where the window is placed with an error to target location. Another important measure of robot performance is the precision. As shown in figure 10, for picking the sidewall panel, it is required that the gripper consistently moves to a same expected position over a period of time, so that picking the panel will be successfully carried. But if there is a problem

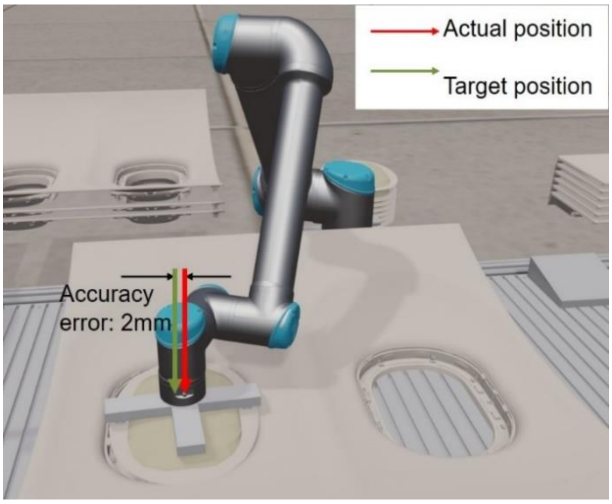

Figure 9: Positional distortion in placing a window

in precision occurs, while picking the panel, the gripper may not move to the same location as expected posing a threat to process execution.

The underlying reasons are described further which is based on the observations from feedback data.

To begin with data analysis for error in end-effector position and orientation, direct inferencing can be made from joint angle data of robots. Comparing the actual joint position vs expected joint position for different time points it would be possible to find the joint, that exhibited different behavior than expected. The underlying reason for such behavior may or may not be directly inferenced. Relations between internal robot parameters such as current, velocity can be easily understood when there are no external disturbances

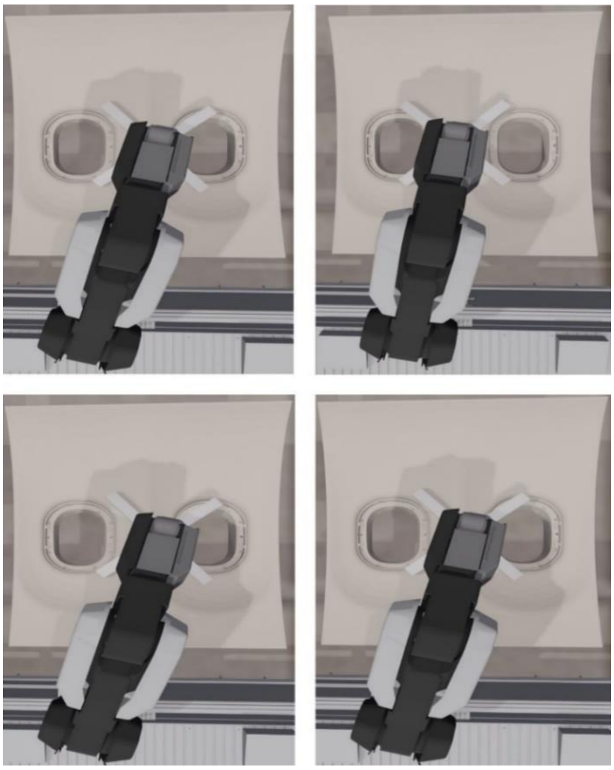

Figure 10: Error with precise positioning of gripper for picking a panel

present in the system. With higher probability of external factors such as vibrations, applied load etc. influencing the robot performance, it is therefore very important to evaluate cross relationships between different sensors information for an effective process planning as shown in figure 11.

5.1 Relating external disturbances and robot parameters

This subsection speaks about relating the external disturbances such as vibration or applied payload to the internal robot parameters. As shown in figure 12 and figure 13, the actual orientation of joint 1 is the reason for positional distortion of the end-effector as shown in figure 10. A similar investigation is carried for all joints to ascertain the faulty oriented joints. At the next level, external disturbances are correlated with the angular position of joint 1, to better understand the behavior. Behavior of applied load and vibration against the joint orientation is studied and interpreted with end-effector position. The influence of the object's mass, shape and/or material properties are inferenced based on the context information. As described in data storage (figure 2), without the knowledge of associated context it would be impossible to understand the reason for sudden change in joint 1 value, as it is due to the

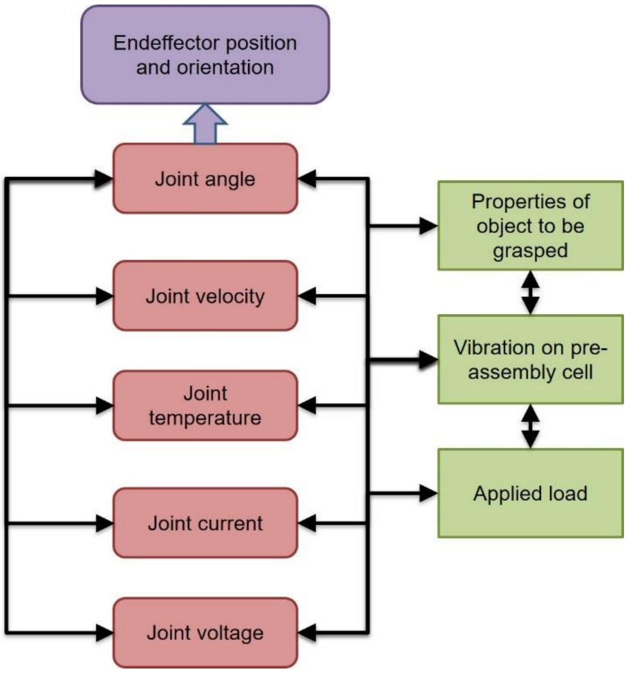

Figure 11: Interrelations between external disturbances and robot parameters

object being handled for a particular operation. Cross relations between vibration and different joint parameters are expressed as well as for the applied load. One such relation between joint 1 position and vibration is shown in figure 14.

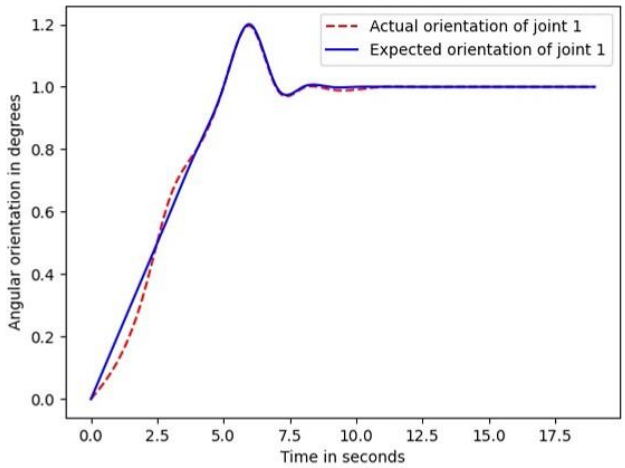

Figure 12: Actual vs expected joint1 orientation

Based on the analysis made between the external disturbances and the internal robot parameters, process planning is improved so that appropriate robot was mapped for appropriate process and object to handle. A lookup table is generated that describes the different robot parameters for handling a component. One such table is given in figure 16, where analysis based on digital shadow is made and the parameters corresponding to handle a hat-rack assembly by two different robots. Importantly, the successful collaborative mechanism with effective process execution time is ensured as depicted in figure 5.

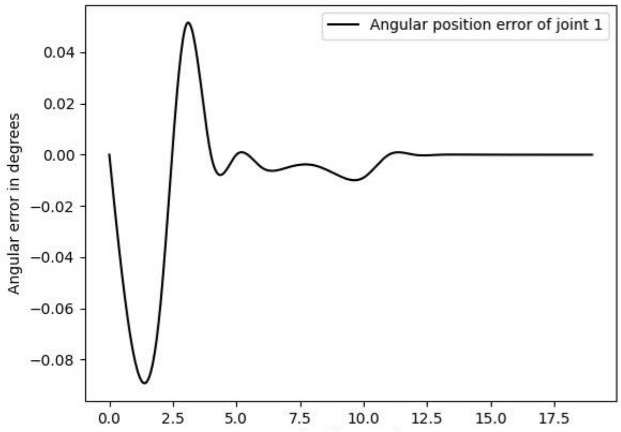

Figure 13: Angular positional error of joint1

6. REPLAYING STORED KNOWLEDGE

To evaluate the effectiveness of the assembly process, it is necessary to replay the stored information in the virtual world, where more information on process parameters can be evaluated. Replaying the assembly events should allow the user to understand the associated process. Therefore, a replay system is implemented, that displays contextual information along with process data. Blender is used for replaying the data, as the software is open-source. The time stamp from HDF5 data is used to create the timeframes in Blender and for each timeframe, the associated robot state is represented by creating appropriate keyframe corresponding to orientation of robot joints. Context information serves as an identifier to understand the associated task as shown in figure 15.

7. CONCLUSION AND FUTURE WORK

In this paper the digital shadow for autonomous robot operations for cabin assembly process is described, where internal and external process parameters on the pre-assembly cell are recorded and analyzed for any deviation in the expected robot behavior. Data acquisition from the pre-assembly cell is done with OPC-UA communication, where an OPC UA client is able to retrieve information from the server. The robot parameters are stored in a binary file, which is later used for analyzing the existing anomalies. The process of analyzing different types of data is described here, but a deeper understanding of other external parameters such as material properties or ambient temperature will contribute to the future work. Based on the complexity of data for any crucial tasks, machine learning algorithms are promising to detect anomalies in the robot performance. Live visualization for remote monitoring is planned for future, where any future process malfunctions could be identified in advance and necessary measures are taken based on past experiences. Visualizing the simulation on Blender looks good, but more value is added when using Webots for robot assembly. This is in initial stage of work, and later generating offline program from Webots/Blender is envisioned based on obtained results. For better sharing of results with OEMs (Original Equipment Manufacturers) in the digital thread, Virtual Reality (VR) application is developed, which currently is in initial stages. Building a digital twin for the process is planned on the future road map to transfer the process knowledge from digital world to real world.

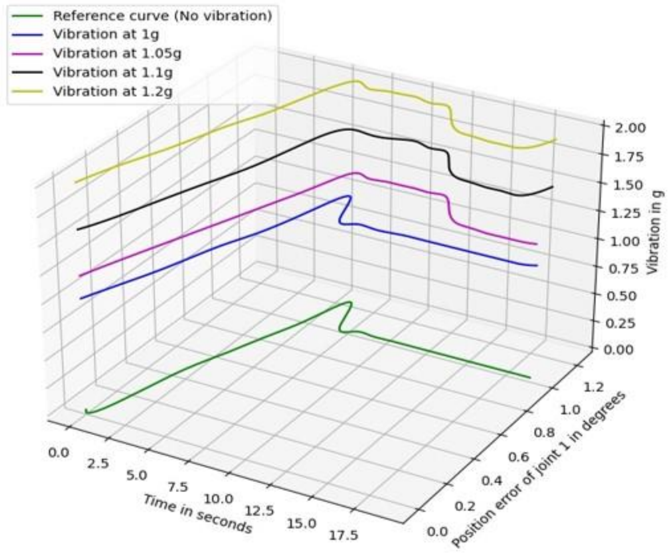

Figure 14: Angular position of robot joint1 at different vibrational frequencies

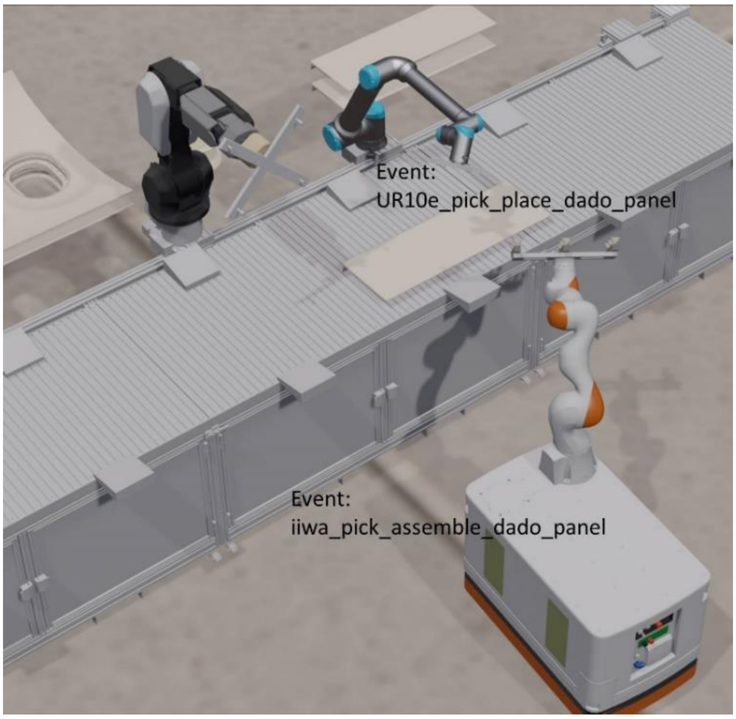

Figure 15: Contextual information for an event

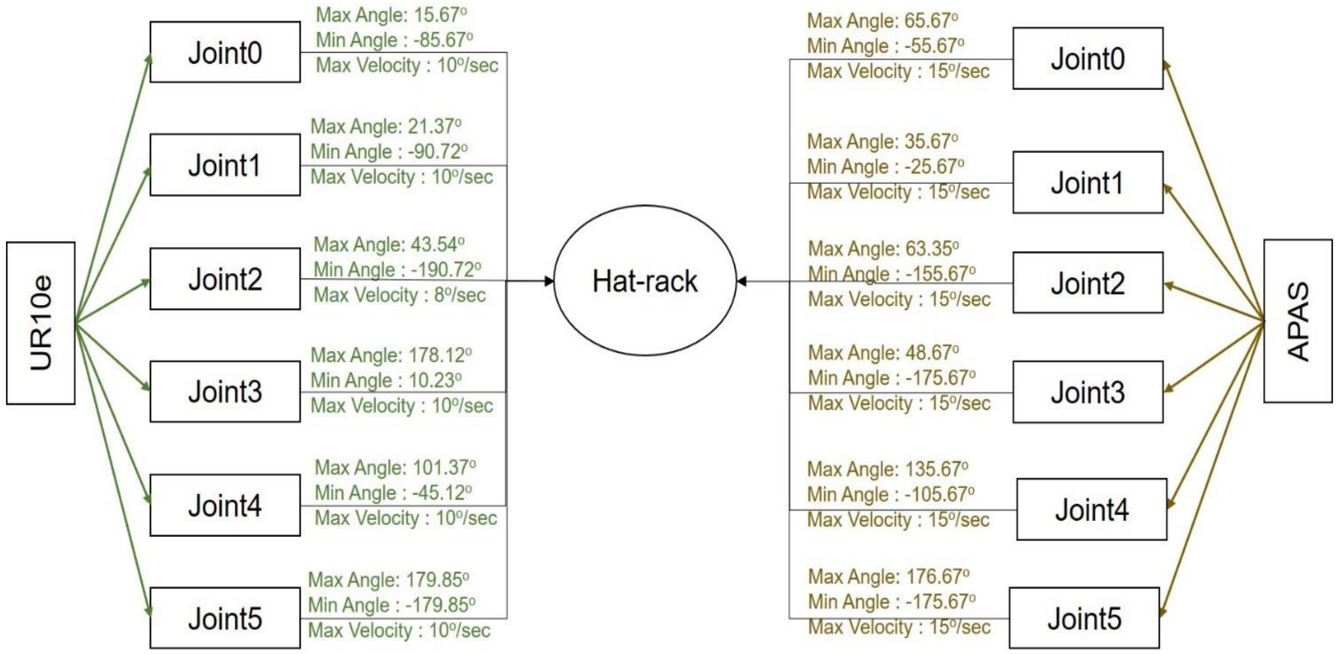

Figure 16: Lookup table for hat-rack component assembly with UR10e and APAS robot

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