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Synchronization Evaluation of Digital Twin for A Robotic Assembly System Using Computer Vision

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Abstract

Traditional production processes are profoundly transforming in the era of Industry 4.0 and smart manufacturing. Smart manufacturing, a core element of Industry 4.0, employs advanced technologies such as automation, robotics, AI, big data analytics, and machine learning to boost productivity and manufacturing performance. Central to this evolution is the Digital Twin (DT), digital replicas of physical assets that blend real-time data with advanced analytics and simulations. Ensuring synchronization between the digital replica and its physical counterpart is crucial for the success of Digital Twins. This paper addresses the challenge of achieving and quantifying synchronization within DTs, focusing on replicating physical system behaviour and measuring deviations or delays. The study delves into the critical aspects of synchronization within digital twin applications, focusing on its implications for a robotic assembly system. The research successfully harnessed YOLOv8 to facilitate real-time event tracking and synchronization characterization, highlighting the potential of computer vision in enhancing synchronization accuracy and, consequently, the efficiency and reliability of manufacturing processes.

Keywords: digital twin; synchronization evaluation; consistency; cyber-physical system; smart manufacturing

1. Introduction

A revolution is underway in the era of Industry 4.0 and smart manufacturing, transforming traditional production processes. Industry 4.0, termed the Fourth Industrial Revolution, integrates cyber-physical systems, the Internet of Things (IoT), cloud computing, and artificial intelligence (AI) into the manufacturing landscape [1]. This integration has given rise to interconnected and autonomous systems capable of real-time communication, data analysis, and data-driven decision-making [2,3].

Smart manufacturing, a core component of Industry 4.0, is dedicated to enhancing production processes through advanced technologies and data-driven strategies. It harnesses automation, robotics, AI, big data analytics, and machine learning to enable proactive decision-making, boost productivity, and elevate manufacturing performance [4,5]. Achieving smart manufacturing necessitates seamless integration, with connectivity as the linchpin, enabling devices and systems to communicate effortlessly. The Internet of Things facilitates the interconnection of sensors, machines, and components, enabling real-time data exchange and insights. Data collection and analytics are equally indispensable, extracting valuable insights, detecting patterns, and empowering predictive and prescriptive analytics from the wealth of data generated by interconnected systems [1–3].

As one of the main parts of Industry 4.0, Digital Twin, conceptually proposed by Michael Grieves [6], represents a digital replica of a physical asset. The application of DT has recently been found in manufacturing, smart homes, greenhouses, mine ventilation, nuclear reactors, and virtual PLCs [7–11], mainly because DTs provide a holistic view of assets, enhancing decision-making and enabling proactive maintenance and optimization by integrating real-time data with modelling and simulation. Also, DT empowers manufacturers to monitor, analyze, optimize performance, predict failures, and test scenarios within a virtual environment before implementing real-world changes.

DTs encounter various challenges; among these, synchronization is a critical concern. In this context, synchronization pertains to aligning activities, processes, or events to occur simultaneously or in a well-ordered sequence. Failure to achieve synchronization between a Digital Twin and the physical system in the manufacturing domain can result in misleading depictions of real-world conditions and performance. Consequently, it can lead to flawed decision-making processes, suboptimal maintenance practices, and inefficiencies, potentially causing elevated downtime and decreased operational effectiveness. These issues, in turn, can potentially trigger production delays and financial losses. In other words, it is a critical factor for ensuring that the digital representation consistently and accurately reflects the state, behavior, and changes occurring in the physical entity. This alignment is essential for maintaining data consistency, enabling dynamic updates, supporting effective feedback loops, and enhancing the predictive capabilities of the digital twin.

Despite the significant repercussions of the lack of synchronization between digital twins and their physical counterparts in manufacturing there is a noticeable absence of studies leveraging machine vision to achieve [12–20].

Digital Twin synchronization ensures real-time alignment between digital twin models and their physical counterparts. Challenges in achieving effective synchronization include continuous and reliable data exchange, robust communication infrastructure, and dealing with latencies. Complex systems with multiple components and subsystems also pose modelling difficulties. Past research has integrated various technologies and approaches to address these challenges, including real-time data streaming, advanced analytics, and visualization software.

Zheng et al. [12] demonstrated digital twin synchronization for construction processes. In manufacturing and robotic assembly systems, digital twin synchronization optimizes production processes, as seen in Alam and El Saddik's [13] work on human-robot collaboration. Qi et al. [14] highlighted real-time integration between physical systems and their digital twins to enhance overall system performance. Zhang et al. [15] introduced a consistency evaluation framework for digital twin shop-floor models, addressing both post-assembly and post-assembly phases, validating the accuracy of these models in representing real-world objects.

Under the paradigm of the DT application in smart factories, Akbarian et al. [16] proposed three controller-system architectures for creating a synchronized digital twin for industrial control systems. The research showed that the controller-system architectures, which integrate the PID (Proportional–integral–derivative) controller and differentiate controller models between the virtual and physical counterparts, had the most outstanding by showing the smallest error and settling time compared to the physical systems' output. Besides, Zipper's work [17] introduced a state-synchronization method for aligning a physical plant with its online simulation by employing static and dynamic optimization. To address real-time performance concerns, the author provided strategies to enhance efficiency without compromising the synchronization performance. The experimental works via a motor demonstration showed prominent results.

In DT research focusing on human-robot collaboration, Liang et al. [18] introduced a real-time robot DT system for human-robot collaboration in construction and digital fabrication. The research addressed a pose-checking algorithm for joint angle synchronization. Results from different case studies indicated the high accuracy and low latency of the real-time performance in the proposed DT system.

In the field of metaverse-related research, Han et al. [21] introduced a dynamic hierarchical framework to tackle the DT synchronization challenge for Virtual Service Providers (VSPs) in the metaverse with the support of Unmanned Aerial Vehicles (UAVs). Researchers applied temporal value decay dynamics to gauge the impact of VSPs synchronization strategies on DT values. The research also employed an evolutionary game to model dynamic VSPs selection behaviors among UAVs via the open-loop Nash solutions. The study demonstrated the stability of equilibrium points in the lower-level game and underscored the superiority of dynamic games.

This conference paper addresses the critical challenge of achieving and quantifying synchronization within the domain of Digital Twins. The research work's specific focus lies in accurately reproducing the behaviour of the physical system and measuring any deviations or delays that may arise.

To achieve this pivotal synchronization and quantification, this paper introduces a novel metric that seamlessly integrates the YOLOv8 (*You Only Look Once*) computer vision algorithm. YOLOv8's prowess in real-time event detection and tracking, especially in the context of a robotic arm, makes it an ideal candidate for this purpose. The approach further involves the creation of a tailored dataset, which, when employed in conjunction with the YOLOv8 model, consistently achieves a good level of accuracy in capturing and quantifying synchronization delays. This metric is a substantial and innovative contribution to the field, effectively addressing the pressing need for characterizing synchronization delays. The versatility of YOLO extends beyond its real-time delay measurement capabilities, offering manufacturers a valuable tool for precise quality control. Through ongoing monitoring and detection of deviations from established benchmarks in synchronization delays, manufacturers can guarantee the fidelity of their digital twins to real-world systems. This, in turn, enhances decision-making, optimizes operations, and provides a competitive advantage within the manufacturing sector. Despite several synchronization methods being addressed in digital twin-related research, there is limited work on evaluating the performance of digital twin synchronization, particularly in the manufacturing field. To address this deficiency, this paper proposes an innovative approach utilizing the YOLO computer vision algorithm, renowned for its object detection capabilities. This method offers a precise and automated means to monitor, measure, and analyze real-time synchronization delays, presenting substantial potential benefits for manufacturing processes.

The paper's structure is organized as follows: Section 2 outlines the proposed methodology, Section 3 introduces the

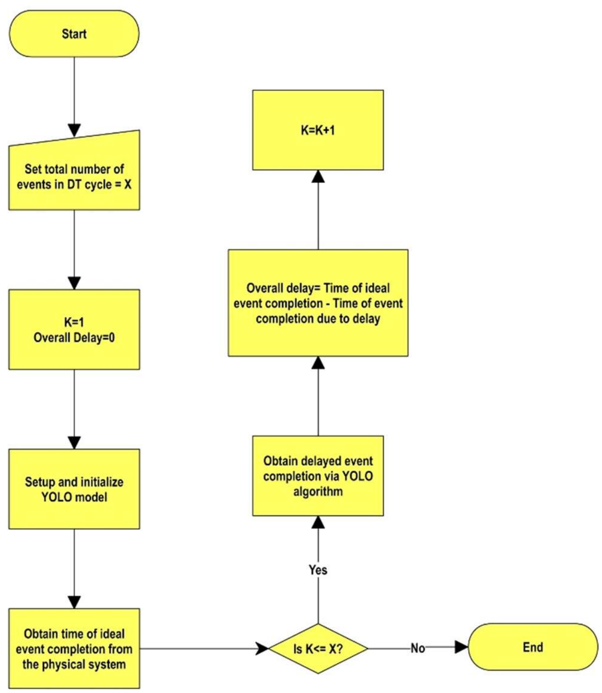

Fig 1. The proposed asynchrony characterization framework with YOLO

Asynchrony Test Protocol, Section 4 is dedicated to analyzing results, Section 5 offers conclusions, and Section 6 outlines potential directions for future work.

2. Methodology

The utility of YOLO extends beyond its real-time delay measurement capabilities. It also equips manufacturers with a tool for precise quality control. Manufacturers can ensure that their digital twin faithfully represents real-world systems by continuously monitoring and detecting deviations from established benchmarks in synchronization delays. This, in turn, contributes to more informed decision-making, improved operational optimization, and a heightened competitive edge within the manufacturing sector.

2.1. Proposed Asynchrony Characterization Framework

The proposed asynchrony characterization framework utilizes the computer vision algorithm to process visual information from the physical twin. This framework breaks down the DT cycle into individual events, employing computer vision for object tracking with timestamps to identify and quantify delays during these events. The applied technique analyzes visual cues and temporal information in image or video data compared to ideal operating conditions. It eliminates the need for manual observation and measurement, enhancing efficiency and reducing subjective biases. This research work has adopted YOLO, a well-established computer vision algorithm, as the core of the characterization framework.

The framework depicted in Fig.1 illustrates an iterative process that calculates the overall delay for each event. It compares the ideal completion time defined by the DT with the actual completion time obtained from the physical twin using computer vision.

The process starts by defining the number of events in the DT cycle, usually denoted as $\boldsymbol{X}$. It employs a variable $\boldsymbol{K}$ to track the current event being processed, initially set to 1, where the overall delay equals to 1. Then, the process sets up and call the YOLO model for object tracking, comprising several sub-steps such as preprocessing event data, inputting data to the YOLO model, processing predictions, and post-processing results to obtain final bounding boxes and class labels.

A critical part of the process is to obtain the ideal event completion time from the DT. Events in the DT are pre-programmed and used as ground truth for real completion times. The process runs the trained YOLO model to determine the real completion time of each event. The model is calculated based on the time a bounding box is placed on the detected event and is timestamped from the input video. The process then calculates the asynchrony for each event and add it to the overall delay, increasing $\boldsymbol{K}$ by 1 to proceed to the next event. The entire process repeats until all events in the DT cycle are completed.

This framework provides a structured methodology to assess and quantify delays in synchronizing between the virtual entity and physical entity within the digital twin, ensuring that the replication of behaviour in the virtual entity remains as faithful as possible.

2.2. The YOLO Algorithm

The YOLO algorithm is integral to the methodology, and thus, it is critical to understand its core components, equations, and loss functions.

$$\mathrm{Loss_T} = \mathrm{Loss_{Loc}} + \mathrm{Loss_{Con}} + \mathrm{Loss_{Class}} \tag{1}$$

As shown in Equation (1), the overall loss function $Loss_T$ is the sum of the localization loss function $Loss_{Loc}$, the confidence loss function $Loss_{Con}$, and the class loss function $Loss_{Class}$ [22].

$$\mathrm{Loss_{Loc}} = \lambda_{\mathrm{coord}}[(x_i - \widehat{x_i})^2 + (y_i - \widehat{y_i})^2] + \lambda_{\mathrm{coord}}\left[\left(\sqrt{w_i} - \sqrt{\widehat{w_i}}\right)^2 + \left(\sqrt{h_i} - \sqrt{\widehat{h_i}}\right)^2\right] \tag{2}$$

The localization loss $Loss_{Loc}$, shown in Equation (2), measures the error in predicting the bounding box coordinates (x, y, width, height) relative to the ground truth bounding boxes. x_i, y_i, w_i and h_i are the predicted bounding box coordinates, and the $\widehat{x_i}$, $\widehat{y_i}$, $\widehat{w_i}$ and $\widehat{h_i}$ are the ground truth bounding box. λ_{coord} is a coefficient used to weight the contribution of the localization loss to the overall loss function.

$$\mathrm{Loss_{Con}} = \lambda_{\mathrm{obj}}\left(C_i - \widehat{C_i}\right)^2 + \lambda_{\mathrm{no-obj}}\left(C_i - \widehat{C_i}\right)^2 \tag{3}$$

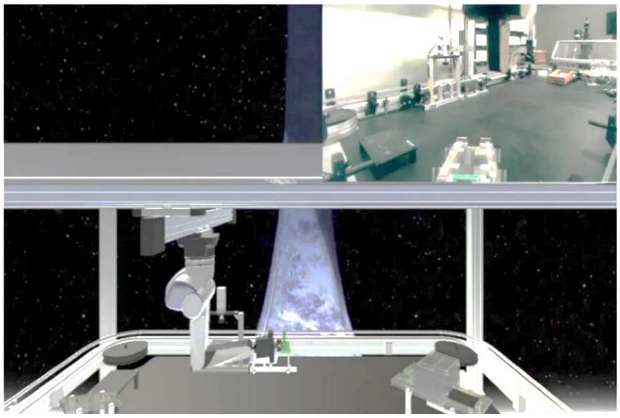

Fig 2. Digital Twin of Robotic Assembly System.

The confidence loss $Loss_{Con}$, shown in Equation (3), measures the accuracy of object predictions, indicating whether the grid cell contains an object or not. It is computed using binary cross-entropy loss between the predicted object scores and the true object scores (e.g., $Loss_{Con} = 1$ if the box contains an object, $Loss_{Con} = 0$ otherwise). C_i represents the predicted objectness score, and $\widehat{C_l}$ represents the ground truth objective score. λ_{no-obj} and λ_{obj} are coefficients used to balance the contribution of the confidence loss to the overall loss function.

$$\mathrm{Loss_{Class}} = \lambda_{\mathrm{class}} \sum_{\mathrm{c} \in \mathrm{classes}} (\mathrm{p_i(c)} - \widehat{\mathrm{p_i}}(\mathrm{c}))^2 \quad (4)$$

The class loss $Loss_{Class}$, shown in Equation (4), measures the error in predicting the class probabilities for each bounding box. It is computed using binary cross-entropy loss for each class separately, comparing the predicted class probabilities with the true class labels. p_i represents the predicted class probabilities, and $\widehat{p_l}$ represents the one-hot encoded ground truth class labels. λ_{class} is a coefficient used to weight the contribution of the class loss to the overall loss function.

The total loss function sums up individual losses and provides the framework for training the YOLO model. YOLO adjusts its parameters by minimizing this total loss during training, enhancing the accuracy of object localization, object prediction, and class probability estimation. This comprehensive understanding of YOLO's loss function is fundamental for the synchronization validation framework, serving as the backbone for object detection and delay measurement.

3. Asynchrony Test Protocol

The Asynchrony Test Protocol outlines the procedures and employs methods to evaluate synchronization accuracy within the digital twin framework for a robotic assembly system. The following subsections will discuss the validation protocol, synchronization accuracy assessment methods, metrics, and criteria.

3.1. Digital Twin for the Robotic Assembly System

This research introduces a sophisticated Cloud-based Digital Twin (CBDT) framework tailored to the intricacies of a robotic assembly system. Such a framework combines cloud intelligence, digital twin modeling, and visualization to improve remote accessibility. They've also developed a prototype system using CBDT for remote monitoring and control of a robotic assembly system as an example of how the framework works [23]. This digital representation is vital to this research work, facilitating event tracking and synchronization assessments. The DT is equipped with a high-resolution visual input system, which captures real-time images and videos of the robotic assembly process. Sensors integrated into the DT provide additional data points, ensuring comprehensive monitoring and synchronization assessment. Additionally, the DT offers a real-time data stream of events, allowing us to compare and validate these events with the physical robotic system.

The physical experimental setup encompasses an array of visual input devices, including cameras strategically positioned to capture critical elements of the assembly process, as shown in Fig. 2. Proximity sensors are employed to detect the presence of Material A and B and collect data relevant to material pickup events. Besides, a switch-based sensor activates the piston during the assembly process. Timestamping of sensor data is meticulously carried out to establish temporal correlations between the digital and physical entities of the robot assembly system digital twin.

3.2. YOLO Model Construction and Tuning

This study relies on the YOLOv8 computer vision model for precise event tracking within the digital twin. This section provides insights into the environment settings, model construction, and fine-tuning.

The YOLOv8 model is constructed and tuned in Python, utilizing the Ultralytics library. GPU acceleration is employed to handle the computational complexity of training the model. Stochastic Gradient Descent (SGD) optimization is chosen because of the small number of event classes (3 events including the material A pickup, material B pickup and assembly pick up. Details can be found in Section 4.3.)

The YOLOv8 architecture, specifically the "Yolov8.1" model, is selected for its capacity to capture intricate patterns and features. The model is trained over 30 epochs and converges at around the 25th epoch. Training parameters and batch sizes are optimized to achieve a Mean Average Precision at Intersection over Union (mAP50) of 0.867. Crucially, the trained YOLOv8 model generates weights saved for later use in event tracking within the digital twin.

3.3. Asynchrony Test Setup

The Asynchrony Test Setup is essential for evaluating the digital twin's ability to accurately track and synchronize events, especially when subjected to real-world challenges.

The primary goal of the asynchrony test is to assess how well the digital twin can adapt and maintain synchronization in

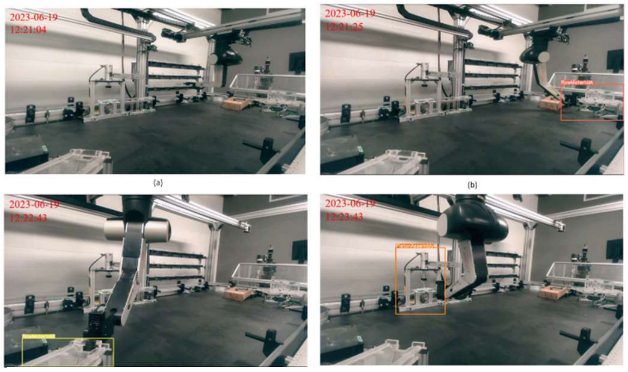

Fig. 3 Object tracking of different robot arm positions (a) home position (b) Raw material A pickup (c) Raw Material B pickup (d) Piston Assembly

the presence of deliberately introduced delays. These delays are carefully crafted to simulate the temporal disruptions that can occur during actual operational scenarios, such as variations in task execution times, dynamic changes in robotic component speeds, or temporary disturbances within the assembly environment.

The asynchrony test relies on the YOLOv8 model as the principal analytical tool to conduct the evaluation. Such a computer vision model continuously monitors the assembly process by analyzing 1080p video footage. This footage captures the assembly proceedings under normal conditions and when subjected to simulated delays, allowing for a comprehensive examination of the digital twin's behaviour under varying circumstances.

To ensure the accuracy of the assessments, the asynchrony test employs a stringent 50% confidence threshold for the YOLOv8 model's detections. This careful thresholding strategy minimizes the risk of false positives or false negatives, ensuring the reliability of the evaluations. Beyond mere observation, the test meticulously measures the durations of key assembly events, including the Material A pickup, the Material B pickup, and the Piston Assembly process. This data provides concrete and empirical insights into the digital twin's performance.

The core of this phase revolves around the thorough analysis of the asynchrony test results. Through systematic comparative analysis, it gains valuable insights into how well the digital twin copes with and compensates for temporal challenges. The digital twin's effectiveness in handling real-world timing variations can be indicated by comparing event durations between standard operational scenarios and those with deliberate delays.

4. Result Analysis

The primary objective of the critical analysis of the synchronization validation experiment is to scrutinize the disparities between YOLOv8-measured and expected delays. This analysis is the linchpin in gauging the accuracy and reliability of the cloud-based Digital Twin framework for the robotic assembly system.

Leveraging the custom YOLO model, valuable information can be extracted regarding both the robot's current sequential event and the duration of said event. The YOLO model outputs are the basis for characterizing asynchrony between events defined in a Digital Twin (DT) cycle. To showcase the efficacy of the proposed method, this research presents a case study involving a robotic assembly system DT.

Following the training phase, the subsequent step involves testing the YOLO model using 1080p video footage of the robotic system, operating under normal conditions with synchronization between events. A confidence rate of 50% was meticulously chosen. The compilation process on Google Colab took 18 minutes and 42 seconds, culminating in the results showcased below in Fig. 3.

The analysis of the results reveals that the time required for Raw Material A pickup is 3 seconds, for Raw Material B pickup is 3 seconds, and for assembly of the piston, it takes 10 seconds. Significantly, these event completion times closely align with the digital twin event completion times, indicating an absence of delay.

However, during the case study, it manipulated the values in the G-code governing the robot arm to introduce asynchrony into the physical system. In this scenario, the YOLOv8 model detected the duration of Material A pickup as 3.8 seconds, Material B pickup as 3.9 seconds, and assembly as 12.75 seconds. The case study calculated an overall delay of 4.55 seconds.

Table 1. Comparison of Event Completion Time.

Event	Normal Operation Conditions (s)	Expected Operating Conditions (s)	Measurement of YOLO (s)	Percentage of Deviation (%)
Material A Pickup	3	3.75	3.8	1.33
Material B Pickup	3	3.75	3.9	4.00
Piston Assembly	10	12.50	12.75	2.00

Table 1 presents a meticulous comparative analysis of three pivotal events within the robotic assembly process: Material A pickup, Material B pickup, and Piston Assembly. For each event, the table delineates essential information:

- Normal Operation Conditions (s): The duration of each event during standard operation conditions.
- Expected Operating Conditions (s): The anticipated delay for each event after modifying the G code.
- Measurement of YOLO (s): The actual duration of each event is measured via the YOLO computer vision-based approach.
- Percentage of Deviation (%): The percentage variation between the YOLO-based measurement and the expected operating conditions for each event.

The data in the table distinctly illustrates the YOLO-based measurement's remarkable alignment with expected operating conditions. Across all three events, namely Material A pickup, Material B pickup, and Piston Assembly, the percentage deviation between the YOLO measurement and the expected conditions remains notably low. Therefore, using computer vision as a synchronization characterization tool for robotic operation system could be a useful tool. It should be noted that the minor difference (0.1 second) in the operation durations detected by YOLO for events of Material A and B pickup is due to the challenge of detecting the sharp starting and end points of events by pictures. This challenge can be further solved in the future work.

5. Conclusions

This study has delved into the critical aspects of synchronization within the context of digital twin applications, specifically focusing on its implications for a robotic assembly system. The key findings and insights within the research underscore the significance of precise synchronization in the digital twin framework. Two principal conclusions can be drawn from the investigation:

(1) The research has successfully applied the YOLOv8 model to facilitate real-time event tracking and synchronization validation within the cloud-based DT framework. This achievement showcases computer vision's potential to enhance the accuracy of synchronization assessments in complex industrial settings.

(2) The analysis affirms the YOLO model's reliability in accurately identifying and characterizing delays in robotic assembly processes by closely aligning with expected event durations. The study reveals that event completion times, such as picking up Raw Material A (3 seconds), Raw Material B (3 seconds), and piston assembly (10 seconds), closely match the digital twin's predictions, indicating synchronization accuracy. However, when intentional asynchrony was introduced through G-code manipulation, the YOLOv8 model identified longer durations for Material A pickup (3.8 seconds), Material B pickup (4 seconds), and assembly (12.75 seconds), leading to an overall computed delay of 4.55 seconds.

In summary, the study emphasizes the significance of synchronization accuracy in advancing digital twin applications, particularly in robotic assembly systems and manufacturing processes. It highlights that achieving synchronization accuracy is not just a theoretical concept but a practical goal with tangible implications for improving efficiency and reliability. The research sets the groundwork for further advancements in digital twins, emphasizing their practical impact on industrial processes.

6. Future Work

While this study has made significant contributions to the field of digital twin applications, it is critical to acknowledge the limitations encountered during the research process. Additionally, avenues for future work and further refinement of the proposed approach should be considered.

(1) This study was conducted under certain computational constraints, which inevitably increased the dataset's size and the training process's complexity. Thus, future research work may need to enhance the approach's scalability.

(2) This study indicates a limitation of YOLO's performance detecting events duration when the collected images have sharpness issues. In such a case, future work may add additional image pre-processing (e.g. image sharpening, edge detection, etc.) before feeding images into the YOLO.

(3) The generalization capabilities of the YOLOv8 model may have been impacted by the relatively limited number of training images. To improve the model's versatility in different situations, future studies can explore techniques that enhance its generalization capabilities.

(4) It would be meaningful to expand the scope of the research to encompass other robotic systems and diverse manufacturing scenarios. Such broader applications can provide insights into the versatility and robustness of the proposed synchronization assessment. The exploration of real-time implementation of the YOLO model, combined with its integration with digital twin frameworks, holds the potential to create more dynamic and responsive systems.

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