

Vision-Enabled Supervisory Feedback Loop for Extrusion Failure Mitigation in Robotic Additive Manufacturing

Hendrik Benz¹, The Vinh Nguyen Trong¹, Kunaljit Chadha², Massimo Visonà³,
and Katharina Klemt-Albert¹

¹Institute for Construction Management, Digital Engineering and Robotics in Construction,
RWTH Aachen University, Aachen, Germany

²Gramazio Kohler Research, ETH Zürich, Zürich, Switzerland

³Erratic, Valdarno, Italy

benz@icom.rwth-aachen.de

Abstract -

Extrusion-based robotic additive manufacturing for construction-scale fabrication is highly sensitive to process faults such as unstable flow, clogging, and fluctuations in feed supply. Without continuous monitoring, these failures can cause prolonged non-deposition and geometric error. To address this limitation, this work presents a vision-guided supervisory framework that couples nozzle-centric process perception with controller-level intervention on an industrial robot. Visual process feedback is obtained from an eye-in-hand RGB-D camera, whose observations are processed online by an instance-segmentation model to classify extrusion behavior. In parallel, motion and process data are retrieved from the robot controller, establishing a common temporal basis between sensed process state and executed robot motion. Upon detection of persistent extrusion failure, the supervisory layer adjusts a bounded program override to reduce or halt robot motion, thereby constraining air-printing duration and facilitating prompt intervention. A proof-of-concept demonstration on an industrial robotic extrusion platform compares nominal reference prints with an induced pump-off failure event in which extrusion loss is detected online and followed by controller action. The results show a practical route toward process-aware supervision without invasive controller modifications and provide synchronized logs for future learning-based methods.

Keywords -

Additive manufacturing; Computer vision; In-process Monitoring; Feedback-Loop; KUKAVarProxy (KVP)

1 Introduction

Additive manufacturing (AM) is increasingly explored for large-scale construction, yet robust and repeatable printing remains challenging due to the interplay of multiple time-coupled sub-processes [1]. These challenges become more pronounced for rheology-sensitive and non-cementitious feedstocks, where process stability depends

strongly on material consistency and environmental conditions [2]. Motivated by reducing embodied emissions of cement-intensive construction, earth-based materials are receiving growing attention as printable alternatives, commonly discussed under the emerging framework of 3D Printed Earth (3DPE) [3, 4]. However, printable mixtures in 3DPE can be highly sensitive to soil composition and moisture content, which affects fresh-state extrudability and build-up performance [5]. Consequently, intermittent flow, clogging, and bonding-related defects can occur during long-duration prints and may remain unnoticed without continuous monitoring [6]. For construction-scale extrusion AM, prior work further highlights that quality assessment should be performed in-process and in-line across multiple scales rather than relying on a single indicator [7].

To overcome the limited availability of practical supervision strategies for extrusion-based robotic printing, this work presents a vision-enabled supervisory loop that detects extrusion state online and triggers controller-side responses to reduce the risk of failing prints. Extending earlier in-process monitoring approaches, this study focuses on integrating near-nozzle RGB-D perception with controller-side intervention in active printing. Robot state variables are streamed from the KUKA KRC4 controller of a KUKA KR210 R3100 via KUKAVarProxy (KVP) and temporally aligned with extrusion-state estimates derived from an eye-in-hand Intel RealSense D405 RGB-D camera. A proof-of-concept experiment demonstrates that detected extrusion-loss events can be followed by adaptive reduction of the program speed override, slowing or pausing motion to enable recovery before major print degradation accumulates. The main contributions are:

- **KVP supervisory interface:** Time-stamped streaming of robot state and read/write access to selected robot variables.
- **Vision-based extrusion monitoring:** Confidence-based extrusion-state detection.
- **Fail-safe intervention policy:** Detect–slow/stop

program-override strategy to mitigate air-printing.

- **Loop-level characterization:** Measurement of detection delay and end-to-end latency (perception → KVP write → override effect) plus qualitative failure-mitigation outcomes.
- **User interface:** Runtime supervisory UI for tuning τ and logging.

As shown in Fig. 1, the experimental platform comprises a pump-fed material supply and a nozzle end-effector mounted on an industrial robot. An eye-in-hand vision sensor observes the nozzle and immediate deposition zone to enable in-process monitoring of extrusion continuity during execution.

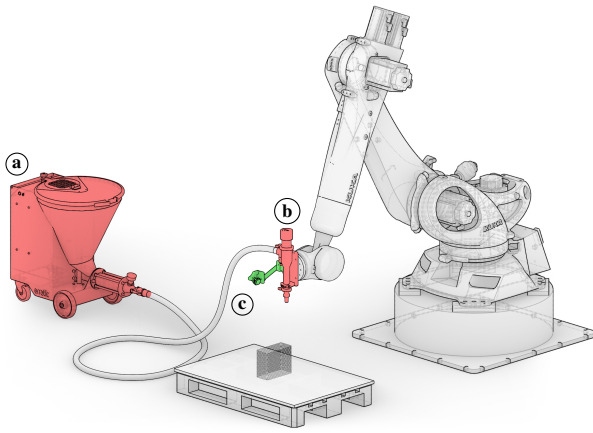


Figure 1. Robotic AM setup: (a) feeder/pump, (b) end-effector/ extruder, (c) eye-in-hand vision sensor.

2 Related work

Large-scale AM has evolved from geometry- and material-centric studies toward integrated pipelines that combine sensing, interpretation, and intervention. This section reviews (1) quality assessment and in-process monitoring for extrusion-based AM and (2) controller interfaces that enable supervisory feedback on industrial robots.

2.1 Quality assessment and in-process monitoring

Quality assessment in extrusion AM can be performed during fabrication (*in-process*) or after completion (*post-process*), and it can be embedded in the production flow (*in-line*) or carried out with separation in time/handling (*at-line/off-line*). In this work, we focus on *in-process*, *in-line* supervision to enable immediate intervention while the robot program is executing.

Table 1 summarizes the monitoring terms used in this paper. We use *in-process* to denote measurement dur-

Table 1. Terminology used in this paper for monitoring and inspection placement.

Term	Description (as used in this work)
In-process	Measurement during fabrication; enables immediate detection/intervention.
Post-process	Inspection after fabrication; verification and documentation.
In-line	Embedded in the production flow; no interruption of execution.
At-/Off-line	Separated from production by handling and/or time delay; delayed feedback.

ing fabrication, and *in-line* for sensing integrated into the production flow without interrupting execution.

Extrusion-based AM comprises interdependent sub-processes whose timing and interaction strongly influence print quality, motivating standardized evaluation and monitoring strategies [1]. For construction-scale extrusion, monitoring is frequently framed as a multi-scale problem where no single indicator is sufficient; instead, assessment should cover material delivery, geometric consistency, and early-age behavior [7]. Early demonstrations of measurement-informed correction further indicate that real-time sensing can support corrective actions during deposition [8].

Vision-based monitoring complements geometric inspection by providing spatially resolved observations around the nozzle and deposited bead. Robot-vision methods have been used to support environment-aware printing and adaptive decisions under non-ideal boundary conditions [9]. For earthen extrusion, monitoring is particularly relevant because material variability (e.g., soil composition, moisture) can affect extrudability, build-up, and interlayer bonding [2, 5]. Frameworks for 3DPE emphasize both sustainability motivations and increased process variability introduced by earth-based feedstocks [3, 10].

Beyond monitoring placement, inspection can also be distinguished by *granularity* (e.g., nozzle-centric point/feature cues versus stage-level or post-print verification); in this work, point/feature cues are used to trigger stage-level supervisory intervention (slow-down or stop) during deposition [7].

Commercial desktop fused deposition modeling (FDM) systems further illustrate camera-based failure detection during printing, where detected anomalies can trigger a pause of the build [11, 12, 13].

2.2 Controller interfaces for supervisory feedback in robotic fabrication

Industrial robot-based fabrication typically relies on supervisory feedback rather than low-level closed-loop control: external sensing triggers discrete interventions such as slowing, pausing, or adjusting process parameters. In

construction printing, this trend is reflected in the shift from measurement-only systems toward monitoring-and-action loops where sensing is explicitly coupled to control signals [8, 7].

A practical barrier is the limited and vendor-specific access to controller state and intervention channels. Available interfaces differ in achievable update rates, integration effort, and required controller-side configuration. For KUKA systems, prior work contrasts KVP and the Robot Sensor Interface (RSI), highlighting timing behavior and trade-offs for feedback applications [14]. Lightweight and open solutions are therefore attractive for research prototypes, as they reduce reliance on licensed options and minimize invasive controller modifications.

Building on these insights, the present work implements a vision-enabled *supervisory* loop using KVP: controller state (e.g., axes, tool pose, process-related globals) is streamed and time-aligned with a vision-based extrusion-state estimate, while interventions are applied via program override. This positions KVP as a pragmatic bridge between in-process perception and controller action for extrusion-failure mitigation in robotic 3D printing [14, 7].

3 Methods

System responsibilities are distributed across the robot controller level, KVP-based variable streaming, RGB-D sensing, and a workstation that performs synchronization, inference, dataset recording, and visualization.

3.1 System workflow and architecture

During execution, the workstation acquires and timestamps RGB-D frames of the nozzle region while concurrently polling KRC4 controller variables via KVP, including joint axes, TCP data, and process-related globals such as \$OV_PRO). Both streams are synchronized, stored in a session-structured dataset, and visualized in a custom interface (Figure 3).

The synchronized observations are subsequently used for extrusion-state classification within a nozzle-centric region of interest (ROI), yielding a binary printing/non-printing signal. Based on this signal, a fail-safe supervisory intervention policy maps sustained extrusion loss to a bounded controller-level action via \$OV_PRO through KVP, thereby slowing or stopping motion to limit “air-printing” and enable timely recovery.

As shown in Figure 2, the system architecture is organized into a robot controller level and a supervisory level. At the robot controller level, the program executes the print motion while robot state variables are made accessible through KVP. At the supervisory level, an RGB-D camera feed is processed by the detection pipeline to determine the current printing state from the nozzle region.

This decision is then mapped to controller action by writing \$OV_PRO via KVP: printing continues under the nominal override, whereas sustained non-printing triggers a reduced override to slow down or effectively pause robot motion.

3.2 Robotic printing platform and sensing

The experimental setup uses a KUKA KR210 R3100 with an Erratic Extruder MS40 supplied by an Erratic Feeder DM80 through a 5 m hose. To observe deposition at the nozzle, an Intel RealSense D405 short-range RGB-D camera is mounted in an eye-in-hand configuration on the robot flange and oriented toward the nozzle and immediate deposition region (Figure 4). This viewpoint captures bead formation and extrusion continuity during motion.

An external workstation serves as the acquisition and logging node. The workstation is a Windows PC that runs acquisition, synchronization, inference, visualization, and dataset recording. RGB and depth frames are streamed from the D405 with per-frame timestamps, while robot state and selected controller and process variables are ac-

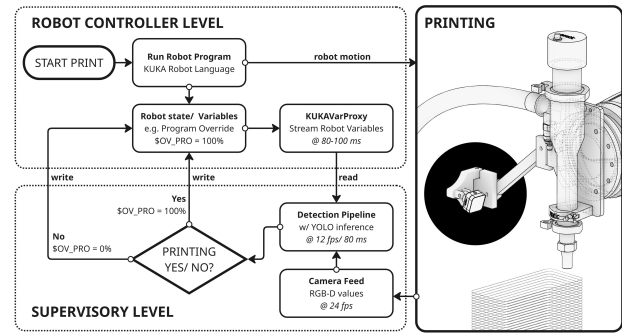


Figure 2. System workflow for vision-enabled feedback-loop: robot controller level, robot motion, KVP-based supervisory level intervention.

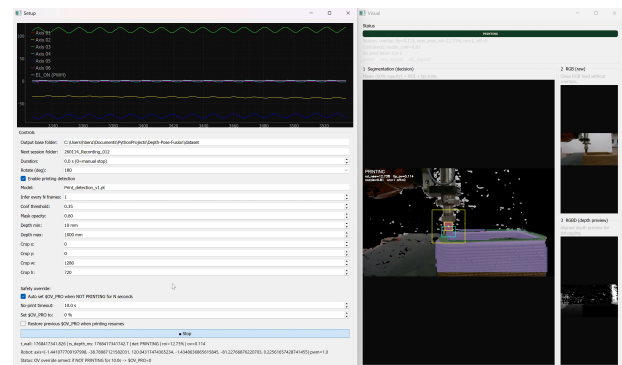


Figure 3. User interface with live extrusion-state inference, ROI overlay, robot-variable plots, logging, and adjustable stop/slow intervention parameters.

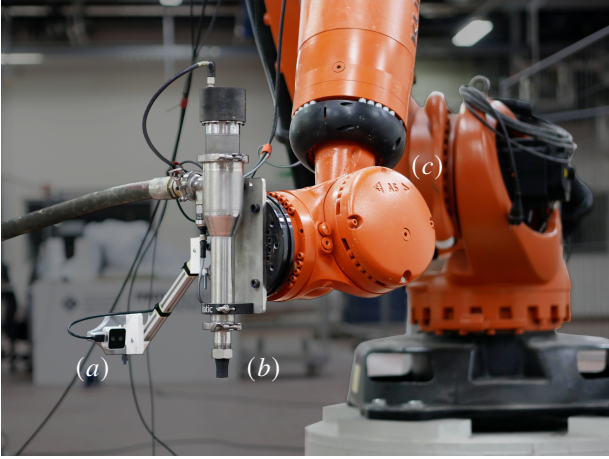


Figure 4. Eye-in-hand nozzle-centric sensing setup: RGB-D sensor (a) mounted to observe nozzle region (b) on the industrial robot (c) for in-process extrusion monitoring.

cessed from the KRC4 via KVP (TCP/IP). Both streams are recorded concurrently in a session-structured dataset, enabling timestamp-based alignment of RGB-D observations with robot kinematics and process state. The overall workflow, including sensing, controller streaming, logging, and the integration of extrusion-state detection with program override intervention, is summarized in Figure 2.

3.3 Controller interface via KVP

Controller telemetry and supervisory actuation are implemented via KVP, which exposes external read/write access to selected KRL global variables and KRC4 system variables over TCP/IP during program execution. Unlike low-level motion interfaces, KVP enables lightweight supervisory feedback through discrete controller-level interventions.

During printing, the workstation polls the controller to obtain time-stamped robot state for contextualization and temporal alignment with RGB-D frames. In the current setup, the logged variables include the joint configuration (A1–A6) and the tool state required to interpret nozzle motion; the interface is extensible to additional process signals (e.g., extrusion rpm, extruder command values) depending on the configured KRL globals. All KVP reads are recorded together with local receive timestamps to capture the as-executed motion state observed by the external supervisor.

Supervisory actions are issued through the same channel using the program speed override `$OV_PRO` as the intervention variable. Upon a sustained extrusion-loss decision, the workstation writes a bounded override value to slow down or effectively pause execution. To ensure stable be-

Table 2. Logged variables, corresponding KUKA controller variable semantics and Description.

Log key	KUKA variable	Description
t_wall	–	Host wall-clock timestamp (Unix s); session reference time.
t_mono	–	Host monotonic time (s); stable for latency measurements.
t_robot	–	KVP interface timestamp associated with each sample.
a1..a6 e1	<code>\$AXIS_ACT.A1..A6</code> <code>\$AXIS_ACT.E1</code>	Actual joint angles (deg). External axis position (unbounded / “infinite” axis). In this setup, E1 encodes the extruder axis position; its time derivative relates to extrusion rate.
ov_pro	<code>\$OV_PRO</code>	Program override / global speed scaling (%).
e_rpm	<code>E_RPM</code>	Derived extruder speed computed from E1 progression (scaled to RPM for visualization/ monitoring).
e_mod	<code>EXTR_MOD</code>	Extrusion modification override (dimensionless scaling factor).

haviour and to avoid excessive controller traffic, override writes are rate-limited and only updated on state transitions (normal $\rightarrow$ intervention, intervention $\rightarrow$ normal). If automatic recovery is enabled, the nominal override value is cached prior to intervention and restored once extrusion is detected again. Overall, KVP provides a practical link between vision-based monitoring and controller-level motion intervention, while keeping the actuation explicit, bounded, and compatible with safety-oriented supervisory control.

3.4 Data synchronization and logging pipeline

All sensing, controller streaming, inference, and dataset logging are executed on a single workstation to ensure a shared time base. The D405 provides synchronized RGB-D frames of the nozzle region, while robot and process variables are polled from the KUKA controller via KVP (KVP) in parallel. The two streams are acquired asynchronously at different rates: KVP samples are queried at an effective update rate of approximately 9.1 Hz (about 110 ms per update), and the camera stream is recorded at 30 fps. To enable consistent multimodal fusion, every sample is timestamped upon arrival at the workstation using (i) a wall-clock timestamp for dataset indexing and (ii) a monotonic timestamp for latency evaluation.

The logger writes a session-structured dataset with three synchronized components: (1) RGB and depth image sequences, (2) a per-frame timestamp table linking frame indices to host and camera time, and (3) a controller-state log containing the KVP samples, like extrusion value E1 (Table 2). Note that E1 is an external-axis position signal that increases along the toolpath; the variable E_RPM represents a scaled speed estimate derived from the rate of change of E1. In post-processing, each camera frame is associated with the temporally nearest KVP sample in host

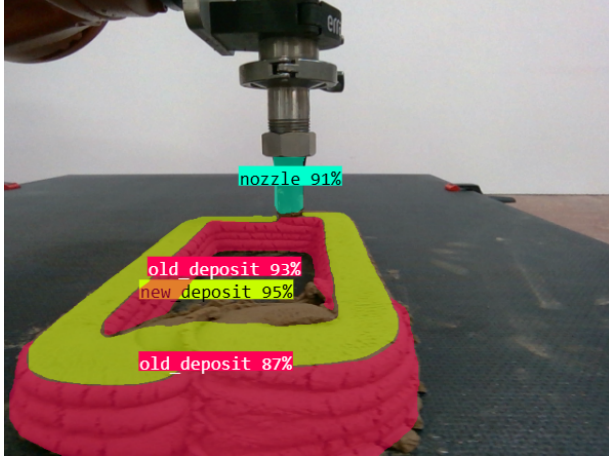


Figure 5. Example YOLOv11 instance segmentation outputs used for extrusion-state inference: nozzle, newly deposited material near the tip (*new_deposit*), and previously deposited layers (*old_deposit*).

time. Associations exceeding a configurable tolerance are optionally rejected to prevent spurious matches under transient delays. This logging design provides time-aligned nozzle observations and robot states for extrusion-state estimation and supervision.

3.5 Vision-based extrusion-state estimation

On top of the logging layer (Section 3.4), a learning-based perception module is trained to detect nozzle-adjacent deposition cues. Recordings were collected under two operating conditions—normal printing and induced extrusion interruption—to capture representative examples of both states. Annotations were managed in Roboflow, and a YOLOv11 instance segmentation model was trained on RGB images to predict three classes: *nozzle*, *new_deposit* (fresh material near the tip), and *old_deposit* (previously deposited layers). Figure 5 shows typical outputs used for subsequent decision logic. In total, 400 images were manually labeled and augmented using geometric and photometric transformations, resulting in 1536 images, which were then split into 92% training, 5% validation, and 2% test data. This setup was used for a fast proof-of-concept validation and to improve robustness under varying conditions, although some augmentation-related correlation risk cannot be fully excluded.

3.6 Supervisory intervention policy

Extrusion supervision is implemented as a rule-based policy that converts vision-derived nozzle-region cues into a controller-level intervention. A YOLOv11 instance-segmentation model predicts instance masks and confidence scores for *nozzle*, *new_deposit*, and *old_deposit* on

RGB frames. At runtime, RGB inference is applied to a depth-filtered crop so that evaluation is focused on the near-nozzle working region rather than the wider surroundings. The decision is then restricted to a nozzle-centered ROI beneath the tool, where fresh deposition is expected.

The intervention logic operates on a binary extrusion-state estimate derived from threshold-based ROI evidence for fresh deposition relative to the nozzle tip. To suppress transient misdetections (e.g., brief occlusions or segmentation noise), the decision is filtered using a persistence window τ . In the current experiments, $\tau = 10$ s bounds “air-printing” while reducing nuisance stops; τ can be adjusted at runtime in the developed user interface to match part geometry and acceptable defect tolerance (Fig. 2), trading faster interruption against a higher probability of false stops.

Printing-state decision. From each frame, compact indicators are computed inside the ROI, including (i) nozzle confidence, (ii) the normalized area of *new_deposit* within the ROI, and (iii) a spatial consistency cue that checks whether *new_deposit* occurs in the expected vicinity below the nozzle tip. A *non-printing* state is declared when the nozzle is confidently detected but *new_deposit* evidence remains below threshold or spatially inconsistent with the nozzle tip region.

Temporal buffering. To avoid spurious interventions from transient occlusions and segmentation noise, the decision is temporally filtered using a sustained-evidence criterion. Let $s_t \in \{\text{print, no-print}\}$ denote the per-frame decision. An intervention is triggered only if $s_t = \text{no-print}$ persists for at least τ seconds (here $\tau = 10$ s, corresponding to $N = \lceil \tau f \rceil$ frames at frame rate f). This buffering prevents short false negatives from interrupting the process.

Controller intervention via override. When sustained non-printing is detected, the supervisor writes a bounded program speed override to the KUKA controller via KVP using the system variable `$OV_PRO`. Override updates are clamped to valid limits and rate-limited to avoid repeated writes in consecutive cycles. If recovery is enabled, the pre-intervention override value is stored and restored once printing evidence is re-established. Figure 6 illustrates the time-lapse behavior, including ROI evaluation, the printing/non-printing overlay, and the resulting override-based slow-down/stop response under extrusion loss.

4 Experiments and Results

4.1 Baseline vs. induced-fault comparison

To demonstrate the proposed supervisory safety layer, we report a proof-of-concept comparison between (i) a nominal reference run and (ii) an induced extrusion-loss

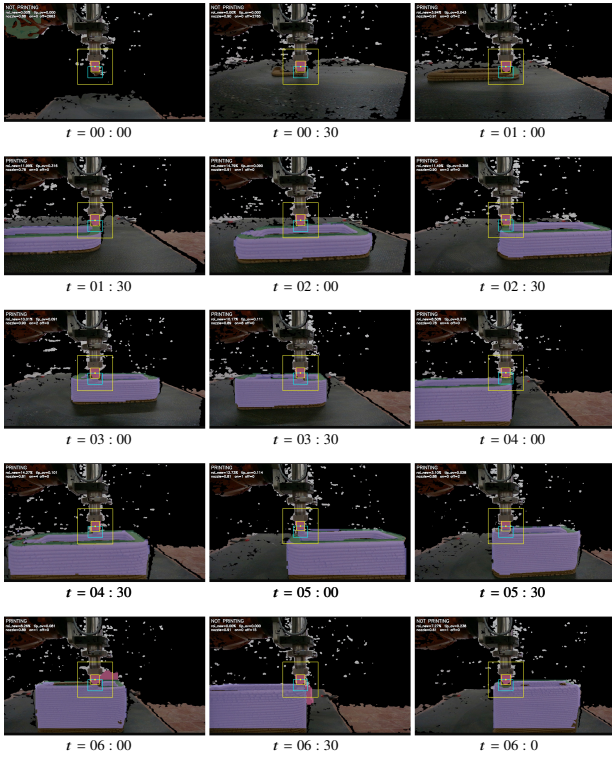


Figure 6. Time-lapse of the vision-based supervisor during printing, showing the RGB-D decision overlay (printing/not-printing) and tracked nozzle ROI; timestamps (t=00:00–06:40) indicate the evolution over the full run till detected failure and program override intervention.

run in which the material pump was switched off approximately halfway through execution. The supervisor monitors the nozzle region and, upon sustained non-printing, writes a bounded program-override command via \$OV.PRO through KVP to reduce motion, thereby limiting continued travel without deposition.

Figure 7 provides geometric context for the failure case. The baseline run (Figure 7a) maintains stable material delivery and produces consistent layer stacking. In the induced-failure run (Figure 7b), turning off the feeder results in progressively under-extruded layers; the final nozzle position indicates where the supervisory loop triggered an override-based stop to prevent further air-printing and to enable recovery actions (e.g., refill or unclogging) before degradation propagates.

While the perspective view highlights the overall geometry, Figure 8 emphasizes the resulting deposition quality. In the baseline case (Figure 8a), bead thickness and layer continuity remain visually consistent. In the failure case (Figure 8b), under-extrusion accumulates over successive layers prior to intervention. Together, the two views illus-

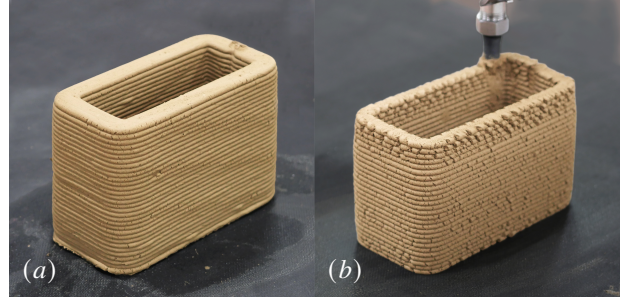


Figure 7. Extrusion-loss comparison: (a) uninterrupted extrusion; (b) induced pump-off event leading to under-extrusion until the supervisor intervenes and stops motion.

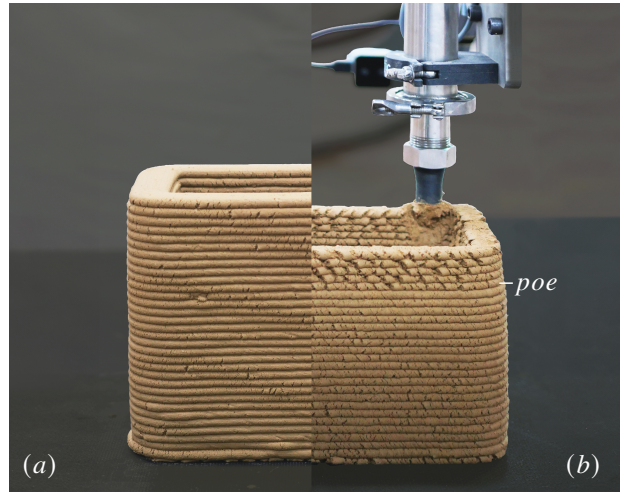


Figure 8. Front-view comparison emphasizing deposition quality differences for the same toolpath: (a) baseline deposition; (b) induced pump-off event (poe) leading to under-extrusion with intervention triggered after detected extrusion loss.

trate that the proposed supervision can prevent extended motion under extrusion loss, limiting the spatial extent of degraded deposition and supporting timely recovery.

4.2 Runtime performance and response behavior

We evaluate the proposed supervisor in terms of (i) runtime throughput and stability and (ii) override-based intervention behavior under an induced extrusion fault. During live operation, the effective end-to-end processing rate (capture $\rightarrow$ inference $\rightarrow$ UI/logging) was approximately 12 fps, below the configured camera capture rate, reflecting workstation compute constraints. Nevertheless, the system operated continuously during the reference and pump-off runs and produced complete, time-stamped logs without dropped-session failures.

In the induced pump-off run, the supervisor triggered a program-override intervention after $\tau = 10$ s of sustained non-printing, reducing motion to limit further travel without deposition.

For the underlying perception module, the YOLOv11 instance segmentation achieved 99.0% precision, 83.9% recall, and 84.3% mAP@50 on the held-out evaluation set. The confusion matrix indicates low class confusion overall, with the dominant errors occurring between *new_deposit* and *old_deposit*, which exhibit similar appearance under the given lighting and surface conditions.

4.3 Validation of the supervisory feedback loop

To complement the proof-of-concept comparison, two small repeated-trial test conditions were evaluated, as summarized in Table 3: a non-stop print test and a stop-test with visible printing degradation. The non-stop test was used to verify that the supervisor does not trigger false interruptions during normal operation, while the stop-test was used to assess whether extrusion loss is detected consistently before visible quality degradation becomes pronounced. Three samples were evaluated per condition as a compact first repeatability check. The results indicate stable behaviour in the non-stop trials and consistent early detection in the stop-tests, supporting the intended role of the loop as an early warning and intervention layer.

Table 3. Repeated-trial timing results for false-interruption screening and early extrusion-loss detection.

Measure	S1	S2	S3
False interruption (non-stop test)	No	No	No
Quality-drop time [s]	26	25	27
YOLO detection time [s]	20	20	20
Lead time [s]	6	5	7

5 Conclusion

5.1 Key contribution and takeaway

This paper presented a vision-enabled supervisory feedback loop for extrusion-based robotic 3D printing that couples in-process perception with controller-level intervention using KVP. An eye-in-hand RGB-D sensor provides nozzle-centric observations, which are converted into an extrusion-state signal and mapped to a bounded intervention through the KUKA program override variable `$OV_PRO`. The loop enables a controller-compatible ‘detect, slow/stop’ strategy that limits air-printing while preserving lightweight integration with industrial robot controllers.

5.2 Constraints and limitations

This study is a proof of concept with limited experimental scope and fault coverage. All experiments were performed on a single robotic platform using one sensor configuration, and extrusion loss was introduced under controlled conditions; accordingly, generalization to other toolpaths, lighting conditions, and material behaviors remains to be established. Runtime performance was limited by the available computing hardware, resulting in an effective inference rate of approximately 12,fps on a Dell Precision 5680 equipped with an Intel i9-13900H, an RTX 4000 GPU, and 32,GB RAM; this reduces the temporal resolution of the perception stream and may lower sensitivity to brief failure events. While higher inference rates would be desirable for broader deployment, the achieved performance was sufficient for the present proof-of-concept demonstration and offered practical value compared with exclusive reliance on human supervision alone.

The supervisory policy is intentionally conservative, requiring extrusion loss to persist for a configurable time window τ before intervention; this improves robustness against transient occlusions and segmentation noise at the cost of a bounded detection delay. Moreover, the current intervention channel is restricted to program override via `$OV_PRO`, providing reliable slowdown/stop behavior but not yet exploiting additional process actuation variables (e.g., `EXTR_MOD` for increasing/ decreasing extrusion rate) for corrective actions such as extrusion-rate compensation.

5.3 Outlook and scaling path

Future work will expand data collection and evaluation by logging full RGB-D streams, controller variables, and intervention events across a broader set of toolpaths and failure modes. This will support quantitative characterization of loop timing, robustness across operating conditions, and sensitivity to the persistence window τ , as well as refinement of the vision model and decision logic.

Beyond pause/stop interventions, the same controller-access setup can be extended toward *corrective* measures. In particular, future iterations will investigate modulating extrusion commands online (e.g., via `EXTR_MOD`) to compensate short periods of reduced flow, and streaming the executed robot motion state to enable localized path-level recovery, such as re-tracing segments or re-depositing under-extruded layers when deviations are detected. These extensions must be designed in strict compliance with applicable safety regulations and risk assessments: once robot motion is altered autonomously, additional safeguards are required, including bounded interventions, limits on axis travel and rotational speeds, and independent safety mechanisms to prevent harm to personnel or equipment. This positions the presented KVP-enabled supervi-

sor as a scalable foundation for increasingly process-aware robotic extrusion AM.

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