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INVESTIGATING JET STABILITY IN INKJET PRINTING THROUGH A NOVEL SENSING MODALITY

Aditya Chivate
Industrial and Systems Engineering
University at Buffalo
Buffalo, NY

Zebin Li
Industrial and Systems Engineering
University at Buffalo
Buffalo, NY

Prachi Ramesh Kamble
Industrial and Systems Engineering
University at Buffalo
Buffalo, NY

Hongyue Sun
College of Engineering
University of Georgia
Athens, GA

Chi Zhou
Industrial and Systems Engineering
University at Buffalo
Buffalo, NY

ABSTRACT

In recent years, inkjet 3D printing has rapidly gained prominence as a disruptive fabrication technique that has witnessed ever-increasing demand in the fields of biomedicine, metal manufacturing, electronics, and functional material production. This innovative approach involves precise deposition of controlled amounts of material onto a moving substrate through a nozzle, achieving impressive sub-millimeter scale resolution by leveraging the concepts of micro-droplet deposition. However, the dynamic nature of the process introduces significant challenges related to consistency and quality control, especially in terms of reproducibility and repeatability. The key input parameters governing this process, such as pressure, voltage, jetting frequency, and duty cycle, are interrelated, entailing the identification of optimal settings in order to realize high-quality jetting. At present, the data collection heavily relies on image-based methods which are inherently slow and often fail to encompass the entirety of the data, making it difficult to determine the relation between the input parameters and jet characteristics. To address this multidimensional difficulty, we developed a unique approach based on light-beam field interruption to collect critical jet data at high speeds. This novel approach collects both temporal and spatial information on droplet evolution, making it a vital tool for enhancing our ability to attain high accuracy and control in inkjet 3D printing. To illustrate the efficacy of our approach, we model the extracted features derived from the process parameters and the extracted data to predict the droplet jetting behavior and droplet size. Specifically, a decision tree classifier is used to predict the jetting behavior and discern between "ideal" and "non-ideal" jetting behaviors. Simultaneously, a linear regression model was employed to predict the droplet size within the "ideal jetting" class based on the interplay of process parameters and the extracted features. The results emphasize the system's accuracy in capturing the droplet behavior and size using our light-beam field interference sensing module. Furthermore, these findings establish a crucial foundation for the implementation of real-time feedback control loop in the inkjet printing process, promising advancements in adaptability and precision.

Keywords: Inkjet Printing, Opto-coupler based Sensing, Latin Hypercube Sampling, Linear Regression

1. INTRODUCTION

Additive manufacturing (AM) is a disruptive manufacturing technology that has garnered increasing attention in recent years and is changing the way we fabricate intricate products. It offers the potential for mass customization, can accommodate novel and unconventional materials, and promotes sustainability. Various AM techniques like digital light projection (DLP), stereolithography (SLA), inkjet printing (IJP), direct ink writing (DIW), and fused deposition modeling (FDM) have found successful adaptations in various applications. Notably, IJP stands out due to its scalability, non-contact nature, cost-effectiveness, ability to incorporate diverse functional materials, and high resolution [1]. Originally associated with graphics and the newspaper industry, IJP has evolved over the past few decades to find applications in a variety of fields ranging from electronics, healthcare, energy, optics, biomedicine, and sensors [2, 3].

IJP possesses a unique ability to precisely dispense controlled picolitre droplets of material, with digital control enabling easy modulation of the output during operation. IJP operates on the general principle of quasi-adiabatic volumetric reduction of the chamber achieved through pulsating input to deposit-controlled amounts of liquid. This chamber-volume reduction can be facilitated by thermal bubble, piezo diaphragm, or solenoid valve. Solenoid valves are gaining popularity due to their low cost and high durability. Amongst the various jetting modes, Drop-on-demand (DOD) is particularly preferred for its ability to achieve high resolution [4]. Droplet formation in DOD is affected by many factors like material properties, jetting conditions, and ambient conditions, making the deposition consistency quite challenging. While the ambient conditions and the material properties remain fixed during jetting, dynamic adjustments to the jetting parameters can contribute to stable and optimized jetting behavior. Input duty cycle, voltage, pressure, and jetting frequency are the key contributors in determining jet stability [4, 5].

Numerous research efforts have been attempted to comprehend the underlying mechanisms of droplet evolution and tackle the quality control challenges in IJP. These efforts can broadly be categorized into physics-based and data-driven approaches. Physics-based models include computational fluid dynamic analysis to measure the dynamic changes in the material properties that influence droplet formation [6, 7]. While these models are capable of offering insights about the process, they are computationally expensive, inherently approximate, and struggle to account for the ambient conditions and deviation in input parameters. Moreover, they can accommodate only a limited number of parameters to avoid modeling complexity thus limiting the comprehensiveness in understanding the jetting behavior. On the other hand, experimental sensing methods provide precise information and insights into the jetting process thus having an edge over the theory-based models.

Data-driven methods have been explored by numerous researchers to gain a holistic understanding of the droplet jetting process. In particular, in-situ data collection has proven effective as it provides a direct measurement of the fluid flow patterns without the need for approximation. Vision-based approaches for in-situ monitoring and data collection have been instrumental in enhancing the quality of inkjet printing. Imaging systems are being utilized to monitor the droplet formation process and study the pinch-off behavior, which is critical in understanding the jet stability [8]. Predictive models have also been developed to determine droplet velocity and volumes using ensemble learning techniques. However, these models rely on static images which fails to capture the temporal information about the droplet evolution. To address these limitations, researchers resorted to using video data of the droplet ejection process to gain a comprehensive understanding of the fluid flow patterns [8, 9]. Compared to the static images, video data can reflect the motion of the flow patterns better and temporal information can significantly contribute to the motion of the observed droplet and its transformation.

While vision-based systems offer numerous benefits, they are inherently slow and computationally expensive to analyze. The inherent nature of the image-capturing paradigms cannot completely capture the fast and dynamic droplet ejection and evolution process. To capture the data corresponding to each pulse, they capture the data at subsequent timeframes that might not correspond to the same droplet. These systems also assume that droplet jetting behavior remains consistent and periodic for a specific set of parameters, making them less suitable for addressing non-periodicity in the jetting. Moreover, video data collection is limited by the camera specifications. Given the high-frequency jetting, collecting each frame is either not possible or requires expensive high-speed cameras. Field-of-view limitations further restrict the amount of collected data. To overcome these limitations, Wang et al. proposed data collection using light-beam field interactions, eliminating the inherent system latency, and enabling true in-situ data collection [10].

Building upon this concept, we introduce 0-DUS (Zero-Dimensional Ultrafast Sensing), as a low-latency sensing modality that works on the principle of light beam field sensing to generate time-series data corresponding to the droplet evolution. This system is capable of capturing data at extreme speeds, thus affording the ability to collect information about each individual droplet. Our previous research has demonstrated effective ways of mapping the time-series data to image data and the process of extracting insights about the speed, shape, size, and stability. The focus of this research is to utilize the time-series data to analyze jetting behavior and develop predictive models that establish a relation between input parameters and droplet characteristics. Each droplet passing through the light beam field generates a voltage spike corresponding to its size, facilitating a more precise and comprehensive understanding of the inkjet printing process. After acquiring the time-series data, extraction of the key features allows for a comprehensive characterization of the jetting behaviors. Besides, integration with machine learning techniques allows the classification of the jet into “ideal” and “non-ideal” jetting, discerning scenarios with and without the presence of satellite droplets. Further, predictive modeling of the droplet characteristics like size based on the process parameters lays a solid foundation for a perspective dynamic real-time process control, promising heightened precision and efficacy in inkjet printing.

2. EXPERIMENTAL SETUP

The novelty and efficacy of our sensing modality lies in both hardware robustness and meticulous calibration. The effective integration of solenoid-valve based jetting system coupled with opto-coupler sensors ensures precise data capture. Calibration enhances reliability and this synergy ensures accurate data acquisition and mapping of the sensor data to tangible droplet characteristics.

2.1 System Hardware

The system hardware is structured around two primary systems: the jetting system and the sensory system. We have employed a solenoid-valve based material jetting system. In this system the solenoid operated valve responds to the applied input voltage and its function is directly influenced by the magnitude of the applied voltage. Additionally, the amount of material dispensed during each pulse is modulated by the applied pressure and depends on the jetting frequency. The solenoid-valve based material jetting system ensures precise and controlled dispensing of material, with the operational parameters closely linked to the applied pressure, duty-cycle, and the jetting frequency. All the experiments were carried out using deionized water as the liquid medium for data collection simplicity.

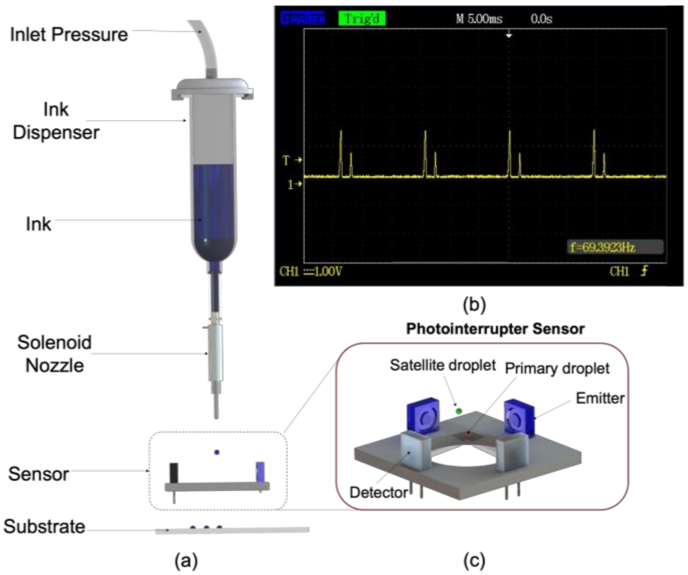


FIGURE 1 (a) SCHEMATIC OF SOLENOID-BASED INKJET PRINTING SETUP AND (c) OPTOCOUPLER-BASED MONITORING SYSTEM (AS SHOWN IN ZOOMED-IN VIEW), AND (b) TIME-SERIES VOLTAGE RESPONSE CORRESPONDING TO A MAIN DROPLET AND A SATELLITE DROPLET PERIODICALLY PASSING THROUGH THE LIGHT-BEAM FIELD.

The second component of the hardware system is the sensory system, responsible for capturing vital information about the jetting droplet. While image-based systems are conventionally employed for this purpose, we have presented a novel opto-coupler based system as shown in FIGURE 1. The opto-coupler system operates on the principle of light beam field interactions and adeptly detects the droplets as they traverse through the light beam field, generating a time-series voltage profile as depicted in FIGURE 1 (b). Opto-couplers have a huge advantage over regular cameras in that they operate at much faster rates. This inherent speed advantage enables real-time data capture, allowing for quick modifications and feedback. This quick reaction time is critical for ensuring consistent print quality. Opto-couplers are also extremely sensitive to changes in light intensity, allowing for the detection of small changes in inkjet droplet behavior. This increased sensitivity allows for the detection of abnormalities and deviations that may otherwise go undetected by standard camera inspection. While cameras generate a large amount of visual data that need lengthy processing, opto-couplers give a more streamlined option by delivering simple time-series voltage data. This not only minimizes computational effort but also speeds up data analysis. Our careful examination of the obtained time-series signal using opto-couplers offered useful insights into the properties of ejected droplets, enhancing our understanding of the printing process, and greatly contributing to the success of our research.

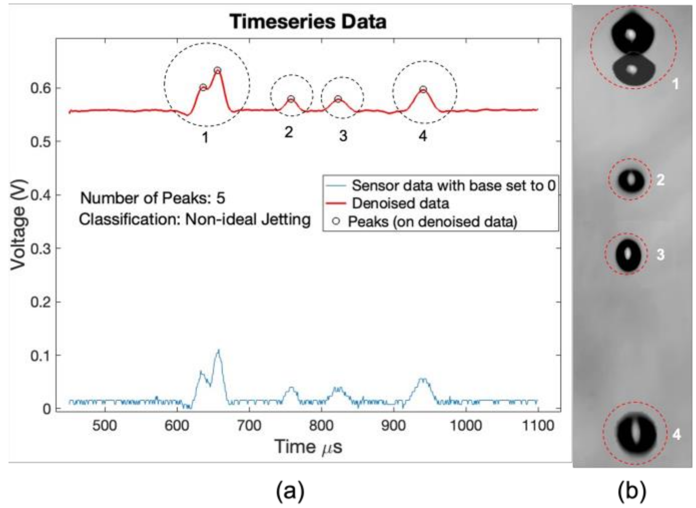


FIGURE 2 (a) TIME-SERIES SIGNAL AS OBTAINED FROM THE OPTO-COUPLER SENSOR (IN BLUE) AND THE CORRESPONDING DENOISED DATA (IN RED) WITH PEAKS REPRESENTING THE INTRUDING DROPLETS, AND (b) JETTING AS OBSERVED FROM THE CAMERA

2.2 System Calibration

Sensor calibration was a crucial step in building the novel anomaly detection system capable of in-situ monitoring. A data driven approach was employed for calibrating the light field spreading, revealing a Gaussian spread pattern. The proposed sensing modality works on the principle of light beam field blocking, where the amount of light being blocked determines the output voltage. Calibration of the voltage-size correlation involved using intruder objects of different sizes, uncovering a saturated voltage reading beyond a certain size due to limitations in the beam size.

Assuming that the droplet reaches terminal velocity and that the light distribution is uniform in all directions, we safely adopt 1D Gaussian representation for determining the size. The location-dependent light spreading led us to an approximating cumulative distribution function of the 1D Gaussian using a sigmoid function given by

$$\boldsymbol{y = a + \frac{b}{1 + e^{-c \cdot x}}} \tag{1}$$

where y represents the voltage response corresponding to the size of the intruding object (x), and a, b, and c are the curve fitting parameters as shown in FIGURE 3. These parameters are adjustable to optimize the fit to collected data. Upon analysis, the collected data indicated that, when voltage is measured in volts and size in millimeters, the curve fitting parameters were determined as follows: a = 0.618, b = 1.23, and c = 3.45.

Equation (1) was used for droplet size determination, considering the non-linear relation between voltage and the amount of light blockage. Validation of the size as determined by Equation (1) and the corresponding image data reveal a root mean squared error of less than 2%, thus ensuring a high prediction accuracy. For the subsequent analysis only the voltage signal data was utilized, streamlining the analytical process.

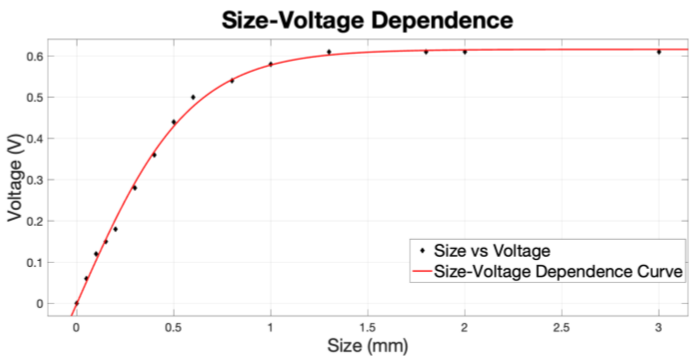


FIGURE 3 APPROXIMATED CURVE REPRESENTING THE SIZE-VOLTAGE DEPENDENCE FOR THE DROPLET

3. DATA COLLECTION AND ANALYSIS

Data collection was performed as two tasks each contributing to the comprehensive understanding of the droplet jetting behavior. The first step involved thorough data acquisition, where the system adeptly captured time-series data corresponding to droplet ejection in response to varying input parameter combinations. The second step focused on the in-depth analysis of the captured droplet data by extracting meaningful insights such as droplet size and number of droplets from the time-series voltage data.

3.1 Construction of DOE Table

A kind of design of experiment (DOE) method, Latin hypercube sampling (LHS), is used for the data collection. LHS hierarchically samples from a multidimensional distribution making it more efficient than random sampling [11]. Table *1* summarizes the range of the process parameters. In total, 50 different parameter combinations are generated. Three repetitions of each experimental setup were performed to ensure robustness of the results.

Table 1 Range of Process Parameters

Process Parameters	Min Value	Max Value
Frequency (Hz)	50	200
Duty Cycle (%)	10	20
Pressure (PSI)	0.5	2.5

3.2 Data Collection and Processing

We employed a pair of opto-couplers to capture the voltage data corresponding to the droplet jetting for each parameter setting. The recorded time-series signal, spanning a stable jet of 10 seconds, was stored as a Excel file for further analysis. To ensure that the parameter combination has taken effect, an initial period of jetting was allowed before beginning data collection. This approach resulted in a substantial data set of over 40,000 data points for each reading, where the number of pulses varied according to the jetting frequency. From the comprehensive time-series dataset, data associated with individual pulses was extracted which served as the basis of our analytical investigations. As demonstrated in FIGURE 1 (b), the interaction between the droplet and the light-beam field generates a discernible voltage spike with the height of the spike proportional to the interruption duration. This important correlation enables us to infer the size of the droplet, with taller spikes indicating larger droplets and smaller spikes signifying smaller ones. Furthermore, the number of pulses in each dataset is associated with the jetting frequency. Some parameter settings result in multiple spikes with varying sizes where the smaller spikes were identified as satellite droplets.

The acquired data pertaining to individual pulses was pre-processed to enhance the clarity of the voltage spikes. Data smoothening was performed to ensure accurate and reliable analysis of the droplet characteristics. Following the initial refinement, signal processing tools were employed to detect and isolate the individual voltage spikes within the time-series data. By identifying these peaks, we were able to determine the number of droplets ejected during the corresponding pulse. The analyzed data was categorized into two distinct subsets (i.e., “ideal jetting” and “non-ideal jetting”) based on the number of spikes observed within each pulse. The first subset, designated as “ideal jetting” was characterized with a singular well-defined spike, indicating a stable and consistent jetting behavior, while the second subset, “not ideal jetting”, includes the cases that jet with satellites or no jetting. FIGURE 2 depicts a case of “non-ideal jetting” where each pulse results in the ejection of multiple droplets. By linking the process parameters (i.e., pressure, duty-cycle, and jetting frequency) to the jetting behaviors, a classification model was built to predict the jetting behaviors which lay a foundation for the droplet control in the future. The “ideal jetting” subset was further analyzed to determine the size of the droplet in consideration. Droplet size is significant in understanding the IJP process, providing valuable insights into the dynamics of fluid flow during jetting. Equation (1), which correlates the voltage data to droplet size, was used for predictive modeling. The predicted size was subsequently validated using image data from the camera, ensuring the accuracy and reliability of the predictions. USB camera (Sentech) with a strobing light was used to capture the image data for jetting behavior validation. Linear regression was used to establish a comprehensive relation between the predicted size and the input parameters like pressure, duty-cycle, and jetting frequency. The details about the data analysis are shown as follows.

3.3 Machine Learning Techniques for Data Analysis

We performed two data analysis tasks based on the parameters and the time-series data, the classification of the jetting behaviors and the regression of the droplet size within “ideal jetting” subset. Two machine learning techniques, decision tree and linear regression were used, respectively.

3.3.1 Decision Tree

Decision tree is a commonly used classification method that recursively splits a dataset into subsets based on the most influential features [12]. At each node of the tree, a decision is made by evaluating a specific feature, and the dataset is partitioned accordingly. This process continues until a certain stopping criterion is met, such as reaching a predefined depth or having a minimum number of data points in a leaf node.

3.3.2 Linear Regression

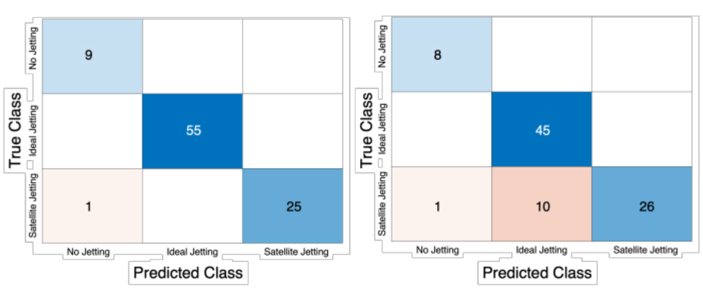
Linear regression is a fundamental statistical and machine learning technique used for modeling the relationship between a dependent variable and one or more independent variables [12]. The method assumes a linear association between the variables, where the aim is to find the best-fit line that minimizes the difference between the observed and predicted values. In essence, linear regression quantifies how changes in the independent variables correlate with changes in the dependent variable.

4. RESULTS

As mentioned above, 50 experiments with different parameters were conducted and the corresponding time-series data were collected. To perform the data analysis, we first split the data into the training dataset and the testing dataset with the ratio of 70:30, then trained the classification and the regression model on the training dataset and tested them on the testing dataset. The results are shown as follows.

4.1 Classification Results

FIGURE 4 (a) shows the confusion matrix on the testing dataset when using the features extracted from the time-series data to perform the jetting behaviors classification. We can observe that the accuracy is 98% for all the classes i.e. “no jetting”, “ideal jetting” and “non-ideal jetting”. This is because the features are the number of peaks and the voltage values, and the jetting behaviors have a strong correlation with the number of peaks. The classification results when using the process parameters are shown in FIGURE 4 (b). It can be seen that the accuracy is good for all the classes i.e. “no jetting”, “ideal jetting” and “non-ideal jetting”, suggesting the feasibility of controlling the jetting behaviors through the process parameters and opto-couplers output using machine learning techniques. In future work, we will further capture the relationship of process parameters and opto-coupler data during process control.

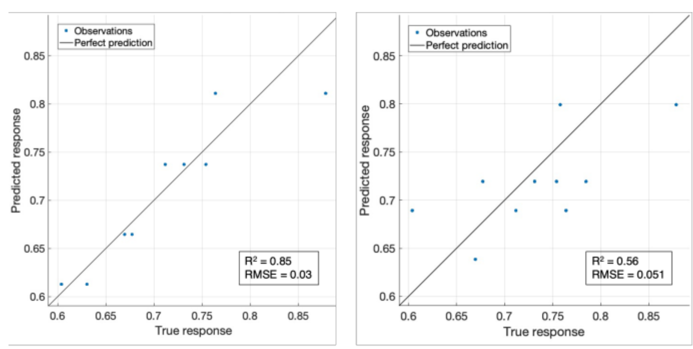


(a) (b)

FIGURE 4 THE CONFUSION MATRIX ON THE TESTING DATASET FOR THE CLASSIFICATION OF JETTING BEHAVIORS BASED ON (A) FEATURES EXTRACTED FROM THE TIME-SERIES DATA (I.E., THE NUMBER OF PEAKS AND THE VOLTAGE VALUES) AND (B) PROCESS PARAMETERS (I.E., PRESSURE, DUTY-CYCLE, AND JETTING FREQUENCY).

4.2 Regression Results

Since only the droplet size for the “ideal jetting” is of interest, we only built a linear regression model using the data from the “ideal jetting” class. After eliminating outliers, 61 data points were used. FIGURE 5 (a) shows the regression results when using the process parameters (i.e., pressure, duty-cycle, and jetting frequency) as well as the voltage values as the predictors. The R^2 and the root mean square error (RMSE) are 0.85 and 0.03 mm, respectively. These results demonstrate the effectiveness of predicting the droplet size based on the process parameters and the voltage values. The regression results when only using the process parameters as the predictors are shown in FIGURE 5 (b). The corresponding R^2 and RMSE are 0.56 and 0.051 mm, respectively. We can observe that by involving the voltage value as a predictor, the regression model has a better performance in terms of R^2. This phenomenon happens since the total dataset is small and adding voltage value as an additional predictor benefits the model. In the future, more experiments will be conducted, and more data will be collected under “ideal jetting”. Besides, the real droplet size will be obtained by using image data captured by the camera to validate the correlation between the droplet size and the voltage value, and the regression model.



(a) (b)

FIGURE 5 THE REGRESSION RESULTS ON THE TESTING DATASET FOR THE PREDICTION OF THE DROPLET SIZE WITHIN “IDEAL JETTING”. (A) THE PREDICTORS ARE THE PROCESS PARAMETERS (I.E., PRESSURE, DUTY-CYCLE, AND JETTING FREQUENCY) AND THE VOLTAGE VALUES. (B) THE PREDICTORS ARE ONLY THE PROCESS PARAMETERS

5. CONCLUSION AND FUTURE WORK

This work presents a novel sensing modality for dynamic drop-on-demand inkjet printing. Our investigation is centered around harnessing the high precision and rapid response of the light-beam field interference as a means of gaining valuable insights into droplet evolution and jetting characteristics in response to the variation in the input parameters. The paper has explored two directions; firstly, it has successfully implemented a decision tree based classifier to categorize the jetting behavior into "no jetting", "ideal jetting" and "non-ideal jetting" classes and furthermore has employed linear regression for predicting the droplet size. The results suggest the effectiveness of using the input parameters and the features extracted from the time-series data in predicting the jetting behaviors and the droplet size. Besides, the results also demonstrate the high accuracy of capturing the jetting characteristics using the developed sensing modality, which holds the promise of online real-time control in inkjet printing process.

The current work is in its nascent stages, paving the way for subsequent advancements in inkjet printing process control. Our next steps would focus on establishing a deterministic relation between various process parameters and their impact on opto-coupler time-series data and overall jetting characteristics. This pursuit aims at uncovering the various interdependencies that govern the printing dynamics. Further explorations will delve into high-speed feature extraction from the real-time process data in conjunction with the predictive models. This holistic approach holds great promise in achieving closed-loop control, where dynamic adjustments can be made in real time based on the evolving printing conditions.

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