Movement Tracking-based In-Situ Monitoring System for Additive Manufacturing

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Abstract. Monitoring and identification of defects during additive manufacturing is mostly done by bespoke optical or acoustic measurement systems. These in-situ monitoring technologies are either intrusive or sensitive to noisy manufacturing environments. We propose a movement tracking-based in-situ monitoring system for additive manufacturing, which is non-intrusive, less sensitive to environmental factors, and easier to operate and maintain. It evaluates the hypothesis that extruder nozzle temperature can be predicted from printer head movement, since temperature and acceleration are correlated due to the printers control unit. Subsequently, this provides an indication of print quality as the extruder temperature plays a vital role. We collected data from experiments using the MakerBot Replicator to examine the hypothesis. Results show that a Random Forest algorithm is more accurate in predicting the temperature variation using head acceleration and time lag temperature data as input parameters, and outperforms a k-Nearest Neighbors and a Vector Autoregression algorithm.

Keywords: In-process monitoring, 3D Printer, Prediction Modelling, Machine Learning, Fault Detection.

1 Introduction

The Additive manufacturing (AM) process assists engineers in optimising designs by reducing material usage and enabling the use of metamaterials with unique microstructures and properties to develop robust and efficient parts. Although AM processes have matured in recent year, various processing defects, low repeatability and inconsistent product quality have slowed down their adoption in industry [1]. Since a failure in one layer can impact the integrity of the entire 3D print, it is vital to monitor in-situ to understand faults and rectify them immediately through a feedback loop during the 3D printing process. Processing-related defects can include cracks, delamination, distortion, rough surface, lack of fusion, porosity, foreign inclusions, and process instability [2]. There are various factors that can lead to these defects such as printing material, product geometry, and process parameters. Fluctuations in process parameters influence the defect rate [3].

To reduce defects, technologies for in-situ process defect monitoring supported by machine learning techniques have been developed for analysing and rectifying defects in real-time AM processes [4]. Most of the proposed monitoring systems are optical or acoustic signal processing systems. However, these systems are either intrusive, i.e., require components to be embedded in the 3D printer, or sensitive to noisy manufacturing environments. In contrast to using optical technologies to identify parts defects by analysing print images, this research aims to utilise optical technology for in-situ monitoring based on print head movement tracking throughout the AM process. Feature recognition and movement extraction from a video stream was investigated along with machine learning techniques to predict the extruder nozzle temperature from printer head acceleration data.

This article details the in-process monitoring technology development and the prediction results. The layout of this paper is as follows: literature review on AM Process defect monitoring, research question and experimental method, experimental set-up, data processing and prediction results, discussion, conclusions, and future work.

2 Literature Review on AM Process Defect Monitoring

Table 1 summarizes techniques developed for AM process defect monitoring, focussing particularly on Extrusion-based AM. Two of the main in-process monitoring techniques proposed in the literature for Extrusion-based AM are acoustic- and optic-based. These technologies include the use of microphones, acoustic emission sensors, cameras, and Fiber Bragg Grating sensors. Machine-learning technologies utilise data collected from these monitoring systems to classify defective parts and identify printer failure states.

Table 1. Techniques developed for Extrusion-based AM process defect monitoring

Reference	Process monitoring equipment	Purpose	Applied machine learning techniques
Wu et al. [5,6]	Acoustic emission (AE) sensor	Identify failure mode and extruder state	K-means clustering semi-Markov model
Delli and Chang [7]	Optical camera	Classify good and defective parts	Support Vector Machines (SVM)
Wu et al. [8]	Optical camera	Detect malicious infill structure	K-Nearest Neighbours (KNN), Random Forest (RF)
Rao et al. [9]	Thermocouples, accelerometers, video borescope	Detection of process failures such as nozzle clog	Bayesian Dirichlet process, Neural Network (NN), SVM
Liu et al. [10]	Optical camera	Identify overfill and underfill defects	SVM
Kim et al. [11]	Accelerometer and AE sensor	Identify healthy and faulty process states	SVM
Faes et al. [12]	2D laser scanner	Assess geometrical error	-
Kousiatza and Karalekas [13]	Fiber Bragg grating sensor	Identify strain fields and temperature profiles	-

The listed literature (Table 1) emphasized the importance of in-situ monitoring in AM. The accuracy of predicting defective parts and printer failure states is high across these published articles. Wu et al. [6] identified normal and abnormal machine states with the accuracy of 91.9 % by applying the hidden semi-Markov model (HSMM) in the acoustic emission time- and frequency-domain features. Wu et al. [8] showed that the Random Forest algorithm detects anomaly in printing infill patterns (seam, irregular polygon, circle, rectangle, and triangle infill) with 96.1 % accuracy using static camera images. Rao et al. [9] identified three process states (i.e., normal, abnormal operation due to insufficient extrusion, and failure to extrude due to nozzle clog) using accelerometers and an infrared temperature sensor. They applied a Bayesian Dirichlet Process (DP) mixture model with the accuracy of 85 %. Liu et al. [10] identified overfill and under-fill defects with the accuracy of 80-90 % by applying Support Vector Machine (SVM) on images collected from a digital microscope. Kim et al. [11] recognized healthy and faulty process states with the accuracy of 87.5 % by applying SVM algorithm on data collected from an accelerometer and an acoustic emission (AE) sensor.

Although the reported accuracy of predicting defective parts and printer failure states is high, all these studies had attached measurement equipment onto the 3D printer. These equipment attachments may itself influence the printing performance, are sensitive to the printing environment, and can be difficult to maintain for permanent use. Acoustic-based systems provide some benefits, such as being lightweight; less costly; providing a high temporal sampling rate (around 5 M samples per second); requiring less processing time than image processing and constituting a less intrusive approach for process monitoring. However, acoustic-based systems have the following limitations:

- The manufacturing factory environment is noisy, with various magnitudes of signals coming from multiple directions which makes it difficult to segregate acoustic signals from different sources. As observed in [6], the threshold parameter plays an essential role in the AE system to detect failures. Identifying thresholds in a noisy environment can be difficult.
- The setting of the AE threshold and further parameters of these systems need to be continuously adjusted because the AE signals are influenced by distance to the sensor. In addition, multiple printing layers and changing part models can generate different AE signals that can be difficult to learn and adapt.
- Robust one-to-one mapping from AE signatures to printing failures and printer state may be challenging, considering the significant overlap across failures and conditions.

Further, some of the challenges observed with optical technologies are:

- The accuracy of defect identification on the layers is greatly influenced by lighting conditions [7].
- The process is intrusive and could lead to changes to the printer's performance due to external attachment.

The discussed limitations highlight a potential research gap in the area of developing non-intrusive technologies that measure important printing parameters to assists in determining failure modes.

3 Research Question and Experimental Method

This research project aims to develop a movement tracking-based in-situ monitoring system for additive manufacturing, which is non-intrusive, non-contact, less sensitive to environmental factors, and easy to operate and maintain. Movement tracking is useful because extrusion temperature mainly depends on the properties of the filament and print speed [14]. Since filament takes time to melt, higher print speeds require higher extrusion temperatures. Based on whether the filament is being pulled through the extruder faster or slower, the extrusion temperature needs to be changed accordingly for better print quality. The main research question addressed in this research is:

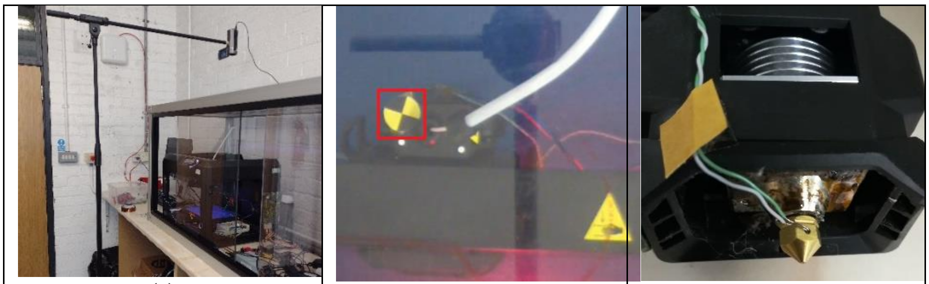
- How well can printer extruder nozzle temperature be predicted using print head acceleration data by utilising machine learning techniques?

The 3D printer head movement was extracted from a real-time video stream using a feature recognition algorithm and used to predict the extruder temperature. In addition to the video stream's acceleration data, we collected head movement acceleration data using an accelerometer for cross-validation. The temperature prediction efficiency was assessed by comparing results obtained from the accelerometer data to results obtained from the acceleration data extracted from the video stream. Three machine learning prediction algorithms were used: k-Nearest Neighbors, Vector Autoregression and Random Forest algorithm. These machine learning algorithms were chosen due to prediction success shown in the discussed literature (Table 1). The study also investigates the effect of incorporating the temperature with a time lag of 0, 1, 5 and 10 seconds on the prediction. The subsequent sections detail the experimental set-up, conducted experiments, and temperature prediction results.

4 Experimental Set-up

We attached acceleration and temperature sensors to a MakerBot Replicator extruder for cross-validation and mounted a video recorder externally above the print head (as shown in Figure 1a. In addition, a crosshair sticker was attached to the printer head to mark its exact position (Figure 1b). This sticker was tracked in the video stream using feature recognition and object-tracking software to compute the print head position, movement, and acceleration. In this work, we compared the accuracy and speed of seven tracking algorithms available in OpenCV [15]: Discriminative Correlation Filter (with Channel and Spatial Reliability) (CSRT); Kernelized Correlation Filters; BOOSTING Tracker; MIL Tracker; TLD Tracker; MedianFlow Tracker; and MOSSE Tracker. The CSRT algorithm was chosen for this particular use case based on the speed and accuracy of tracking coordinates.

The extracted movement tracking coordinates were converted into acceleration data. An ADXL335 3-axis accelerometer was used to record print head acceleration at 1 kHz frequency. A Digilent Pmod TC1: K-Type thermocouple module with wire expansion module was used to measure temperature at 45 Hz (Figure 1c). Samsung OIS DUO camcorder was used to record video. The video was recorded with full HD 1920 x 1080 pixels and 50 frames per second. We conducted three 3D printing experiments that printed the same part in different sizes and printing positions (detailed in Table 2). The reason for setting up three experiments of the same part in different settings was to verify the variation in extruder temperature prediction based on print head movement. The comparison across the three experiments provides a measure of prediction robustness. The data collected from temperature and acceleration sensors and movement coordinates extracted from the video stream were used in the prediction approaches.



(a) (b) (c)

Fig. 1. (a) Experimental set-up, (b) Print head movement tracking, (c) Thermocouple extruder nozzle attachment

Table 2. 3D Print Description

Print Experiment No	Print Name	Description
1	Original	A cylinder with a diameter of 30 mm and a depth of 10 mm was printed at the centre bed location.
2	Original Displaced	A cylinder with a diameter of 30 mm and a depth of 10 mm was printed at a bed location offset by 60 mm to the x and 40 mm to the y dimensions from the centre.
3	Original 25% Shrunk and Displaced	A cylinder shrunk in the size from the original shape by 25% was printed in the displaced location (i.e., offset in the x and y dimensions by 60 mm and 40 mm, respectively, from the centre).

5 Data Processing and Prediction results

We used sensor-based and video-tracking-based acceleration data from the experiments described above to predict extruder nozzle temperature. Sensor-based acceleration data provides acceleration of both, printer bed and head, in each of the three dimensions (x, y and z), whereas video-tracking-based data provides acceleration data in two dimensions (x and y). The data from these sources was synchronised for a second-by-second prediction, which resolved the issues of varied data collection frequencies. For this prediction, statistics (i.e., min, max, mean, variance) from input data from every second of each 3D print were generated and used as input features. With these statistics, we composed four different data columns, tracking the state of each acceleration data source in every second (e.g., the minimum of printer bed acceleration measurement taken in x dimension in second t). The resulting dataset was a multidimensional time series dataset. The mean extruder temperature was then selected as the predicted variable.

To understand the effect that dynamic tracking of the printing status has on the prediction quality, we added time-lagged variables which provide data from previous seconds as additional features to the dataset. In other words, time lagging provides a short memory from which the prediction method can benefit. This short memory has been found useful in prediction across various domains. For example, Nan et al. [16] introduced a three second lag to predict the energy consumption of an electric bus with a Long-short-memory neural network. We obtained prediction results with no time, one second, five seconds and ten seconds lagging, where the past data was introduced as input features in prediction. Note that depending on the length of this short memory, the total number of input features will vary and increase proportionally. For example, when predicting the mean extruder temperature in second t with p seconds time lag, we consider the measurement of the input feature tracking and the minimum of printer bed acceleration in x dimension in second t, and also consider its measurements taken in seconds *t-1, ..., t-p*.

First, the prediction results are presented considering both printer head acceleration data collected from the acceleration sensor and acceleration data extracted from the video stream. Then, the prediction results considering only the acceleration data extracted from the video stream are presented and discussed. Table 3 shows the prediction results with various time lags and considers a 2-fold, 5-fold and 10-fold cross-validation on each printing experiment. We used three different prediction methods: vector autoregression (VAR), random forest (RF) and k-nearest neighbour (kNN) algorithms. We implemented VAR in Python. In VAR, the predicted variable is represented as a linear function of past lags of itself and past lags of the other variables.

So, representing the mean extruder temperature in second t with Y_t, and the measurement of acceleration-based input feature k in second t with X_t^k, we have under p seconds time lag with I acceleration input features.

$$Y_t = \sum_{n=1}^{p} \beta_n^Y Y_{t-n} + \sum_{k=1}^{I} \sum_{n=0}^{p} X_{t-n}^k \beta_n^k$$

With the part of the data used for training, whose size depends on the number of folds selected, VAR fits the coefficients of the input variables via solving $\beta = (X^T X)^{-1}(X^T Y)$, where X is the matrix containing all input variables (past values of the mean extruder temperature and the current and past values of acceleration-based input features) and X^T is the transpose of this matrix.

For implementing RF and kNN algorithms, we used the scikit-learn Python machine-learning library. For kNN, we set its number of neighbours to 10, while keeping the other parameters in their default settings. Random Forest is an ensemble machine learning algorithm that takes input from multiple decision tree predictors. In our implementation of RF, we fixed its number of trees to 200, using mean squared error as the quality criterion for tree splits and setting the minimum number of samples required to split to two samples.

Table 3. Temperature Prediction Results (average R^2 scores from cross-validations).

		2-fold CV			5-fold CV			10-fold CV		
Exp. No	Time Lag	RF	VAR	kNN	RF	VAR	kNN	RF	VAR	kNN
1	0	0.93	0.55	0.61	0.93	0.53	0.61	0.93	0.53	0.63
1	1	0.99	0.99	0.94	0.99	0.99	0.95	0.99	0.99	0.95
1	5	0.99	0.99	0.95	0.99	0.99	0.95	0.99	0.99	0.96
1	10	0.99	0.99	0.95	0.99	0.99	0.96	0.99	0.99	0.96
2	0	0.75	0.10	0.46	0.79	0.12	0.52	0.10	0.78	0.51
2	1	0.96	0.94	0.76	0.97	0.92	0.79	0.97	0.92	0.79
2	5	0.96	0.93	0.77	0.97	0.96	0.79	0.97	0.95	0.79
2	10	0.96	0.67	0.78	0.97	0.91	0.80	0.97	0.90	0.81
3	0	0.68	-0.61	0.40	0.73	-0.57	0.42	0.75	-0.31	0.44
3	1	0.97	0.96	0.74	0.97	0.97	0.78	0.97	0.97	0.78
3	5	0.97	0.54	0.83	0.97	0.97	0.83	0.97	0.97	0.83
3	10	0.97	0.32	0.84	0.97	0.90	0.85	0.97	0.92	0.85

The temperature prediction results show that RF performs well and achieves significantly better results than VAR and kNN. Moreover, its accuracy is robust; it provides a high prediction quality across 2-fold, 5-fold and 10-fold cross-validations, all three experiment instances, and time lags. Examining the effect of time lagging reveals that not only RF but all prediction methods benefit from introducing features data from previous seconds. Nevertheless, we observed that with 10 seconds lagging that VAR can become unable to predict under the 2-fold cross-validation. Since the number of input features becomes very large with a very long-time lag, this might hinder the prediction ability of this method. In particular, when the number of training instances is small compared to the number of features, as with the 2-fold cross-validation, prediction models may not be trained well to predict accurately. In our case, VAR is sensitive to this. However, we must note that RF does not face this problem. The reason for this could be the feature selection ability of RF when it constructs its decision trees; unlike VAR, which is a regression method, RF does not have to include all features in its model. Figure 2 demonstrates the prediction accuracy using the RF algorithm.

Although prediction accuracy is higher, we see that the print specifications impact the prediction methods' ability to predict the extruder temperature. With the original shape, RF can attain an R^2 score up to 0.99; however, with the displaced shape experiment, this drops to 0.97. Note that also for VAR and kNN, we observe a drop in the prediction accuracy in the second and third experiments compared to the first experiment printing the original shape. The results indicate the print location and the specific shape printed by the 3D printer impact the ability to predict extruder temperature from its movement. Also, the results highlight that the time lag information play important role in prediction compared to validation folds, which leads to similar results across folds.

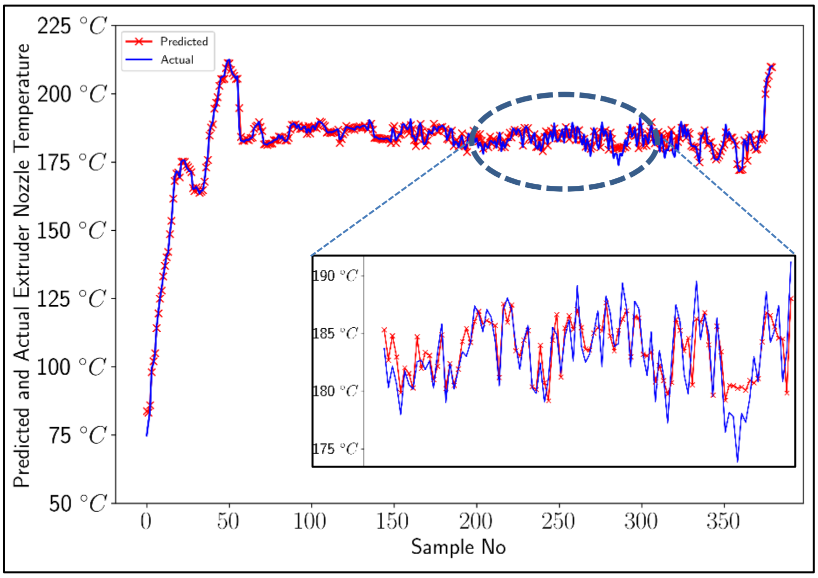


Fig. 2. Comparison results between predicted and actual temperature for experiment number 1 with 5-fold validation and 5 seconds time lag using the RF algorithm.

Table 4. Prediction Results without Sensor-based Acceleration Data (average R^2 scores from cross-validations).

Exp. No	Time Lag	2-fold CV RF	2-fold CV VAR	2-fold CV kNN	5-fold CV RF	5-fold CV VAR	5-fold CV kNN	10-fold CV RF	10-fold CV VAR	10-fold CV kNN
1	0	0.33	<0	0.22	0.31	<0	0.21	0.32	<0	0.24
1	1	0.99	0.99	0.96	0.99	0.99	0.96	0.99	0.99	0.97
1	5	0.99	0.99	0.95	0.99	0.99	0.95	0.99	0.99	0.95
1	10	0.99	0.99	0.93	0.99	0.99	0.93	0.99	0.99	0.93
2	0	0.12	<0	0.10	0.13	<0	0.09	0.12	<0	0.09
2	1	0.95	0.94	0.87	0.95	0.92	0.88	0.95	0.92	0.88
2	5	0.96	0.87	0.81	0.96	0.94	0.82	0.96	0.93	0.82
2	10	0.95	0.81	0.72	0.96	0.92	0.74	0.96	0.94	0.74
3	0	0.26	<0	0.26	0.30	<0	0.29	0.30	<0	0.29
3	1	0.96	0.96	0.86	0.96	0.97	0.87	0.96	0.97	0.87
3	5	0.97	0.75	0.81	0.97	0.95	0.82	0.97	0.94	0.82
3	10	0.97	0.75	0.76	0.97	0.83	0.79	0.97	0.88	0.79

The acceleration data derived from video tracking has the potential to be used as standalone data for predictions, avoiding need for other sensor data. To investigate this in terms of the impact on the prediction quality concerning the extruder temperature, we calculate R^2 scores from RF, VAR and kNN without the sensor-based acceleration data features. Table 4 summarises the prediction results without sensor-based acceleration data. Comparing these results to Table 3 shows that as long as there is time lagging and that past measurements are included as input features in the prediction, comparable results can be obtained without the sensor-based acceleration data. Comparing the three tested prediction algorithms to one another, as in Table 3, we find that RF provides the best quality predictions, and it is more robust. For example, VAR can give very poor predictions (with R^2 scores below zero) when there is no time lagging, whereas with RF we can still obtain reasonable quality predictions. The result suggests that the benefit of using a short memory with the available data can compensate for the potentially detrimental effects caused by not having sensor-based acceleration data.

6 Discussion and Conclusion

In contrast to the in-situ monitoring technologies proposed in the literature, this work presents a non-intrusive movement-tracking-based monitoring system for additive manufacturing. The proposed system extracts the print head position from a video stream, converts print head movement into acceleration data, and utilises machine learning algorithms to predict extruder nozzle temperature. The perceived advantages of this system are less sensitivity to environmental factors, ease of operation and maintenance, and not requiring specialised hardware. The prediction of extruder temperature is chosen since it plays an important role in predicting print quality and process failures, such as nozzle clog [9], and is influenced by the print head movement [14]. The important results from extracting movement data from three experiments are:

- The Random Forest algorithm could predict the extruder temperature well by only using the acceleration data derived from video tracking. The RF prediction is well above 0.95 R^2 score for all three experiments conducted, with at least one second time lag temperature information as an input feature.
- The RF prediction accuracy results are robust considering the high prediction quality across 2-fold, 5-fold and 10-fold cross-validations, all three experiment instances, and time lags.

Although the prediction results establish the viability of the proposed technology, the notable limitation observed is with the no time lag information. Therefore, the ongoing and future research to develop this technology further are:

- Creating a process parameter and print defect knowledge base and regularly updating it as the printer ages could be a potential learning option for improving the prediction.
- Since the extruder nozzle temperature prediction could lead to identify printing process states and faults in printed parts [9], further experiments will be conducted by stimulating print failures and exploring the prediction of them along with failure reasoning abilities.
- Ongoing prediction research involves improving the second-by-second to millisecond prediction, thereby improving the temporal and spatial resolutions to identify the defect locations more precisely.

- Develop a closed-loop control system to in-situ adjustment of correct temperature or print head movement speed using printer Application Programming Interface (API) and controller such as a Proportional-Integral-Derivative (PID) controller.
- Compare the effectiveness of the proposed system to other systems reported in the literature and explore possible other technologies, such as using pulse train data collected from the stepping motor for prediction.

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