A Machine Learning approach to material classification in Additive Manufacturing

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Abstract

The objective of this work was to develop a machine learning (ML) system for automatic identification of the filament type used by Fused Deposition Modelling (FDM) 3D printers. This system, in conjunction with other assessments, could be used in additive manufacturing (AM) as a monitoring and quality control tool during 3D printing process. The major advantage of this approach is that monitoring of the printing process can be performed in a simple, completely non-invasive way, without having any additional impact on the printing process. This system can be implemented for real-time control monitoring on the layer-basis by independently processing data acquired for a single layer and, as a result, issuing a warning if type of the filament has been changed during printing process.

In this report, a methodology developed with aim to recognise usage of different filament type than the one predefined in the parameter settings during printing of a sample design is presented. The methodology consists of a set of techniques employed to acquire and process the sensor data, compute a set of specific task-related features and classify data according to the filament type used. In order to prove the concept, an experiment was designed and performed on the FDM printer to collect data for analysis. Preliminary test results of the proposed and implemented ML system evaluated from the experimental data demonstrates the detection rates of 82-97%. The achieved results represent the initial steps in development of an automated real-time system for controlling filament type in the FDM systems.

1. Introduction

Fused Deposition Modelling (FDM) is the most commonly used 3D printing technology nowadays. It is used to build 3D objects from 3D computer-aided design (CAD) files for use in design verification, prototyping, development and manufacturing. An object is built layer by layer by selectively depositing melted material according to a pre-determined path. This technology was invented by Steven Scott Crump in 1989 and commercialized a year later by Stratasys. Since then, the FDM 3D printers have tremendously advanced, became of the desktop size and more affordable and, in most cases, are the first 3D printers to which we are exposed to. Now, the desktop size printers are transitioning to the professional market space, more than 50% of them is sold to the companies of all sizes [1]. There is a projection that the FDM industry will continue to increase from 25.61% of the global market in 2017 by 0.5% in market share.

Regardless of a continuous increase in usage of the metal in additive manufacturing (AM) industry [2], the plastic materials are still the most used ones as they are more convenient both for prototyping and production due to their physical properties, cost efficiency and practicality. These materials are able to withstand high stress and temperature, they are durable, water resistant and flexible. The two nowadays most popular thermoplastic filament materials in desktop 3D printing are PolyLactic Acid (PLA) and Acrylonitrile Butadiene Styrene (ABS) [3]. PLA is environment friendly and easy to use, while ABS is known for its impact resistance and toughness. They are also available in a large choice of colours and can be effortlessly post-processed.

Since the physical properties of the filament materials are different, the set of instructions and parameters given to the FDM 3D printers must be altered accordingly even for the same CAD file to accommodate for these changes. Thus, using different filament type with a parameter set optimised for another filament would affect both process of printing and the quality of final built part. To overcome this issue of accidentally changing filament type during the printing process, there is a need for in-situ monitoring of the printing process and providing an alert if such situation happens.

2. Method

The block scheme illustrating the methodology proposed in this study is shown in Figure 1. Time-series sensor data used in this work were acquired during printing a small sample design (25 mm × 25 mm × 20.85 mm) on the FDM 3D printer. The STL design file was predefined for Acrylonitrile Butadiene Styrene (ABS) as a default filament of choice and exported to a binary X3G file using the firmware software. All data recordings were then collected during printing from the same design file with the unchanged set of printing parameters (e.g. layer thickness, infill, temperature of the platform and extruder). The equal number of recordings (30) were made for three different cases: (i) using ABS filament, (ii) using PLA, and (iii) with no filament present (NF), consisting the dataset of 90 recordings in total (Table 1). To ensure repeatability of the conducted experiment, the measurements for these three cases were taken in random order ensuring that the sensors positions, printer and ambient conditions are kept approximately same. Each recording was represented by approximately 12-minute-long time series data and stored for offline processing purposes.

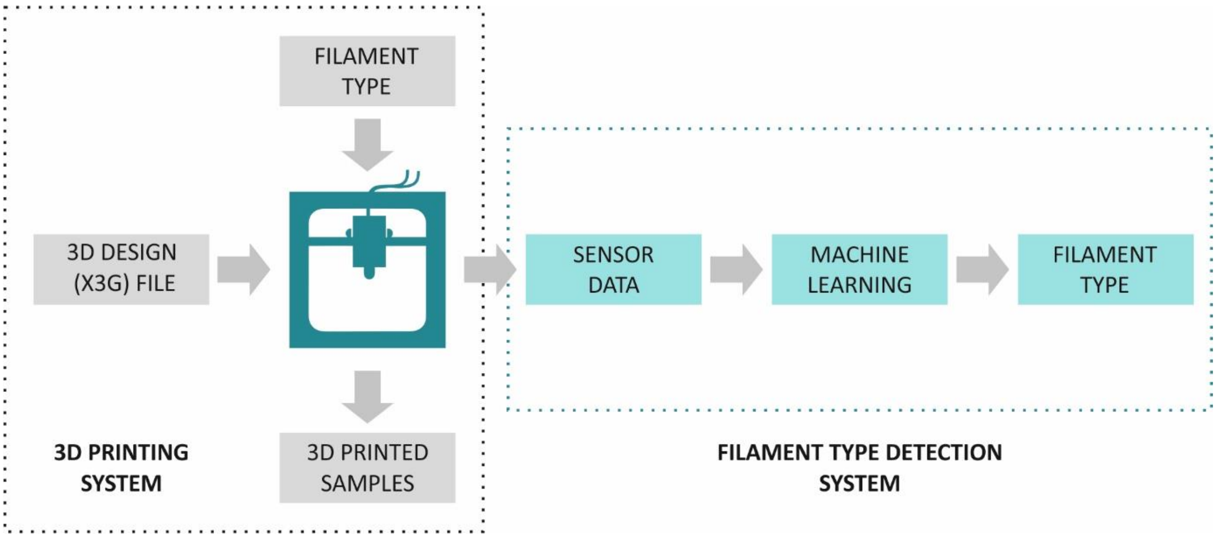

Figure 1. Block diagram of the proposed method

All signals recorded in the dataset were initially time-aligned (using the autocorrelation function to estimate delay between them) and pre-processed to eliminate noise and less relevant frequency ranges. As shown in Figure 2, a chosen sample design has varying structure across the layers, so sensor data reproduce specific design parameters as well as different layouts of each layer of the printed sample. To account for changes across the layers and to investigate their effects on the ML system performance, the recordings were divided into non-overlapping consecutive segments of equal length. For each individual segment, a feature vector holding both temporal and spectral features was generated. The feature matrix was then formed of the feature vectors calculated from the corresponding segments using the total number of recordings. All features were standardized to have a zero mean and unit standard deviation (z-score normalization) prior to being used in a feature selection process. This procedure reduces the dimension of the system by eliminating features with little or no predictive information and can also provide better accuracy due to a smaller sample size used. The significance of each feature, in terms of its ability to separate the classes of interest, was assessed using an independent evaluation criterion. The significance scores were calculated from the data used for training the ML system and the key features were ranked accordingly. A subset composed of the best-ranked features selected for each fold individually was then used to classify the test data.

Table 1. Description of the recorded datasets

Set	Material	Specifications	No of recordings
ABS	Acrylonitrile butadiene styrene	Hatchbox Silver ABS 1.75 mm	30
PLA	Polylactic acid	Verbatim White PLA 1.75mm (Verbatim 55268)	30
NF	–	No filament used	30

(a) (b)

Figure 2. Samples printed using two different filament types: (a) ABS and (b) PLA

Statistical classification methods considered in this work belong to a group of supervised learning methods, where some knowledge about the data is available and is used during training to produce an inferred function that maps the input features to an output class and which can then be used for classifying unlabelled data. A leave-one-out cross-validation was applied, i.e. the system was trained using a subset of the best ranked features selected from the N–1 recordings and validated on the single remaining recording. This process was performed on each data segment independently and the overall classification performance was calculated as an average across all segments. The system performance was estimated using the following list of metrics: accuracy (ACC), sensitivity (SEN), specificity (SPEC), positive predictive value (PPV), negative predictive value (NPV), the Mathew's correlation coefficient (MCC) and F1 score. Moreover, the worst and the best performance of the system (i.e. minimum and maximum values of the achieved accuracy) as well as its variation across all segments (i.e. standard deviation of the achieved accuracy) are also given.

3. Results

The feature significance scores were computed for each segment independently allowing the ML system to account for time-variations in the data patterns due to changes in the design and geometry over the layers. An illustration of these changes is given in Figure 3 for the 10 s long data segments (approximately the duration of printing one layer). It is shown that only a relatively small number of features remain highly ranked across the time, i.e. are independent of the variation in the geometry of the printed sample while the scores of the most of other features change over the time, i.e. across the data segments. This highlights ability of the ML system to adapt to the variations over time.

The most occurring best ranked features presented in Figure 4 demonstrate significant difference between ABS recordings and PLA and NF recordings considered together. Also, the level of separation between them does not significantly change over time.

The accuracy of the proposed system obtained for all tested datasets using four different segment lengths (10, 30, 60 and 120 seconds) is given in Table 2. For the case of finding either PLA or no filament from the default filament type (ABS), the accuracy increases from 79.8% for 10 seconds to 86.4% for 120 seconds long segments. Moreover, variation over all data segments in this case was the smallest (3.4%) with accuracy varying from 83.3% to 90.0% depending on the data segment analysed.

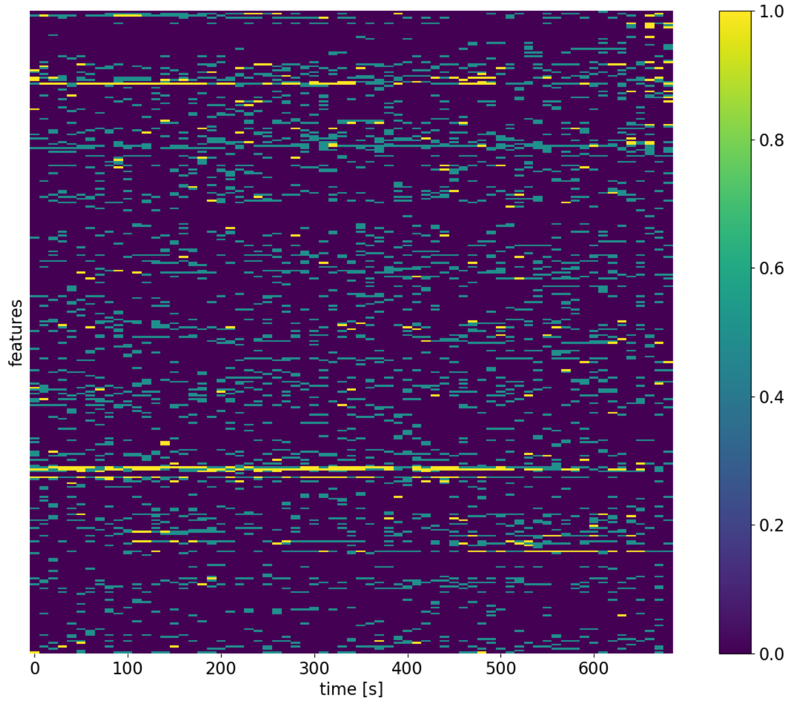

Figure 3. Time-variations of the features significance scores

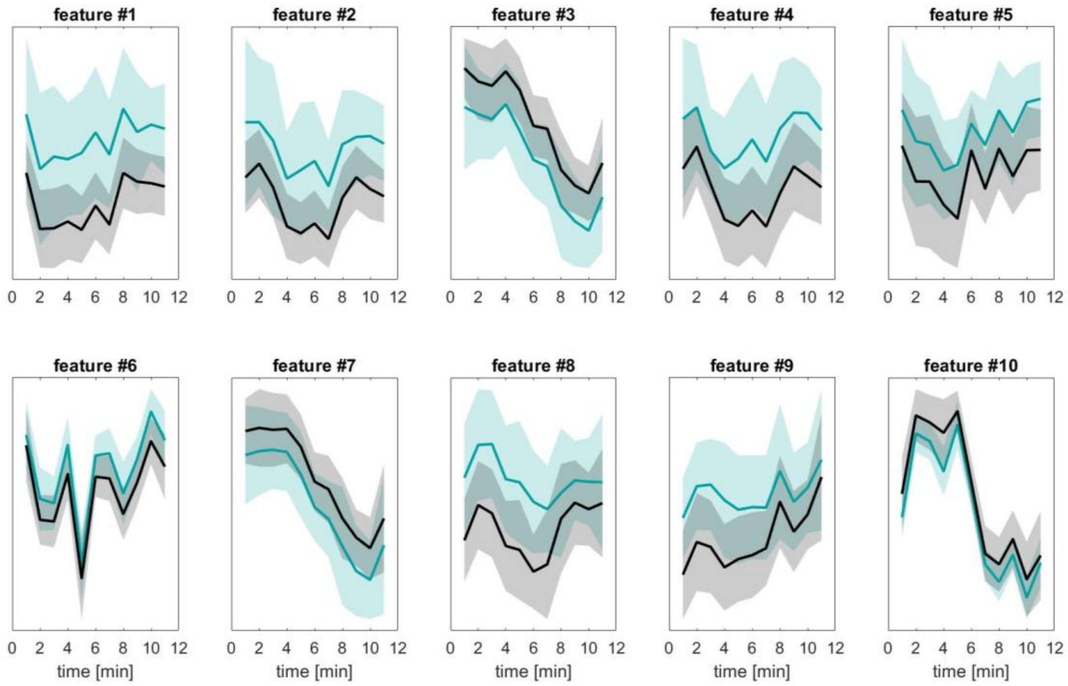

Figure 4. Separation between the best ranked features extracted for ABS and two other cases (PLA+NF) across the time. The mean±std are marked with green (ABS) and black (PLA+NF) solid line and shaded areas respectively.

Table 2. Accuracy achieved for different segment lengths

Datasets	**Segment length [s]**	**Accuracy [%]** min	max	mean	std
ABS vs (PLA+NF)	10	61.11	98.89	**79.76**	6.76
	30	73.33	87.78	**82.61**	4.07
	60	76.67	95.56	**84.55**	5.15
	120	83.33	90.00	**86.44**	3.37
ABS vs PLA vs NF	10	77.04	94.81	**84.57**	3.30
	30	80.74	91.11	**86.34**	2.92
	60	79.26	91.85	**87.81**	3.53
	120	86.67	92.59	**90.07**	2.20
PLA vs NF	10	83.33	100.00	**93.89**	3.61
	30	85.00	98.33	**94.57**	3.11
	60	91.67	98.33	**95.45**	1.98
	120	91.67	100.00	**97.00**	3.21
ABS vs NF	10	78.33	98.33	**88.84**	4.47
	30	83.33	96.67	**90.80**	4.38
	60	83.33	96.67	**90.15**	3.76
	120	85.00	93.33	**89.33**	3.25
ABS vs PLA	10	61.67	98.33	**78.65**	6.65
	30	70.00	91.67	**81.96**	6.15
	60	80.00	88.33	**83.33**	2.58
	120	71.67	90.00	**82.00**	6.60

The values of accuracy obtained for individual segments of different length are shown in Figure 5. The results demonstrate that usage of longer segments yields smaller variation of the system accuracy over the time as well as higher overall accuracy for all datasets. The results achieved for the longest segment of 120 seconds are summarised for all tested datasets in Table 3.

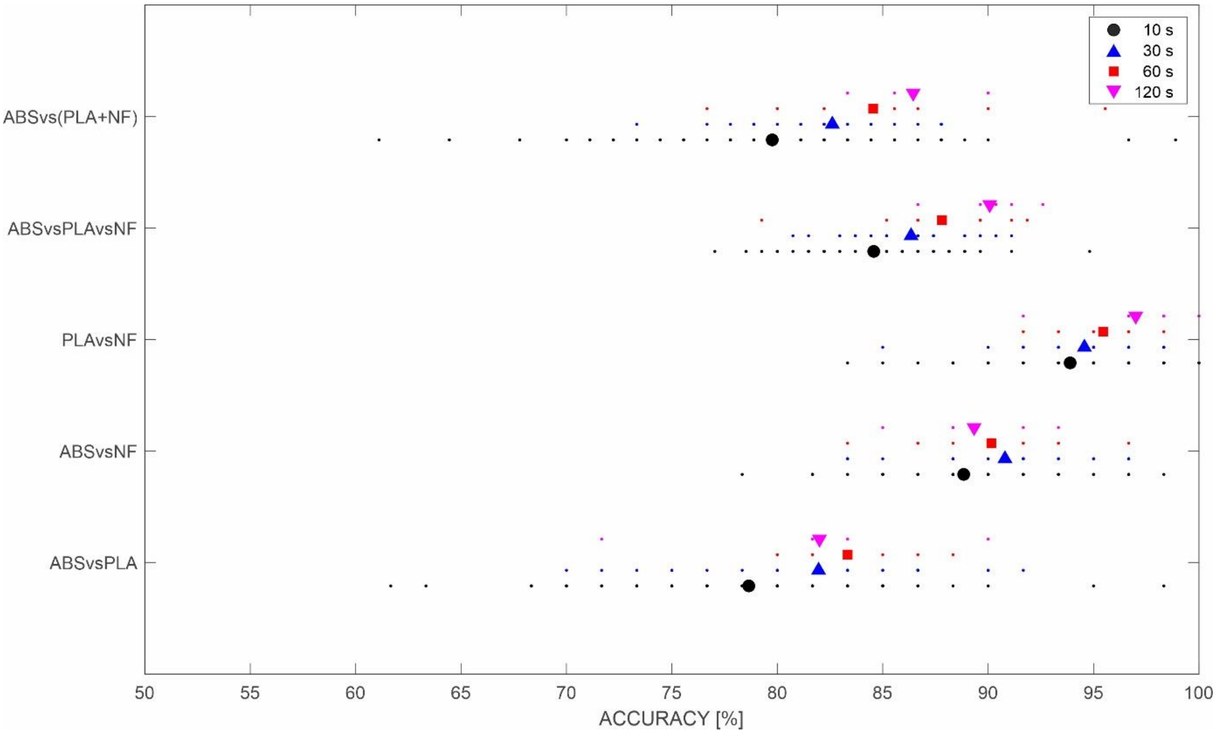

Figure 5. Accuracy of the ML system for different lengths of data segments and datasets (average values across all segments are presented with markers in different colours)

Table 3. Overall performance of the proposed system for the segment length of 120 s

	ACC [%]	SEN [%]	SPEC [%]	PPV [%]	NPV [%]	MCC	F1 score
ABS vs (PLA+NF)	**86.44**	92.00	75.33	88.27	82.40	68.97	90.07
ABS vs PLA vs NF	**90.07**	85.11	92.56	85.11	92.56	78.18	85.11
PLA vs NF	**97.00**	99.33	94.67	95.04	99.26	94.15	97.11
ABS vs NF	**89.33**	94.67	84.00	85.81	94.18	79.33	89.91
ABS vs PLA	**82.00**	86.00	78.00	79.44	85.36	64.40	82.51

To demonstrate ability of the proposed system, several faulty samples were also printed with default ABS filament missing or being misplaced certain time after the printing start. The result of detecting these cases shows that the number of incorrectly detected segments decreases for longer segments from 3-4 for 30 s to only 1 incorrect 60 s segment. For the cases presented in Figure 6, the achieved accuracy was 90.9% for the 60 seconds and 100% for 120 seconds long segments.

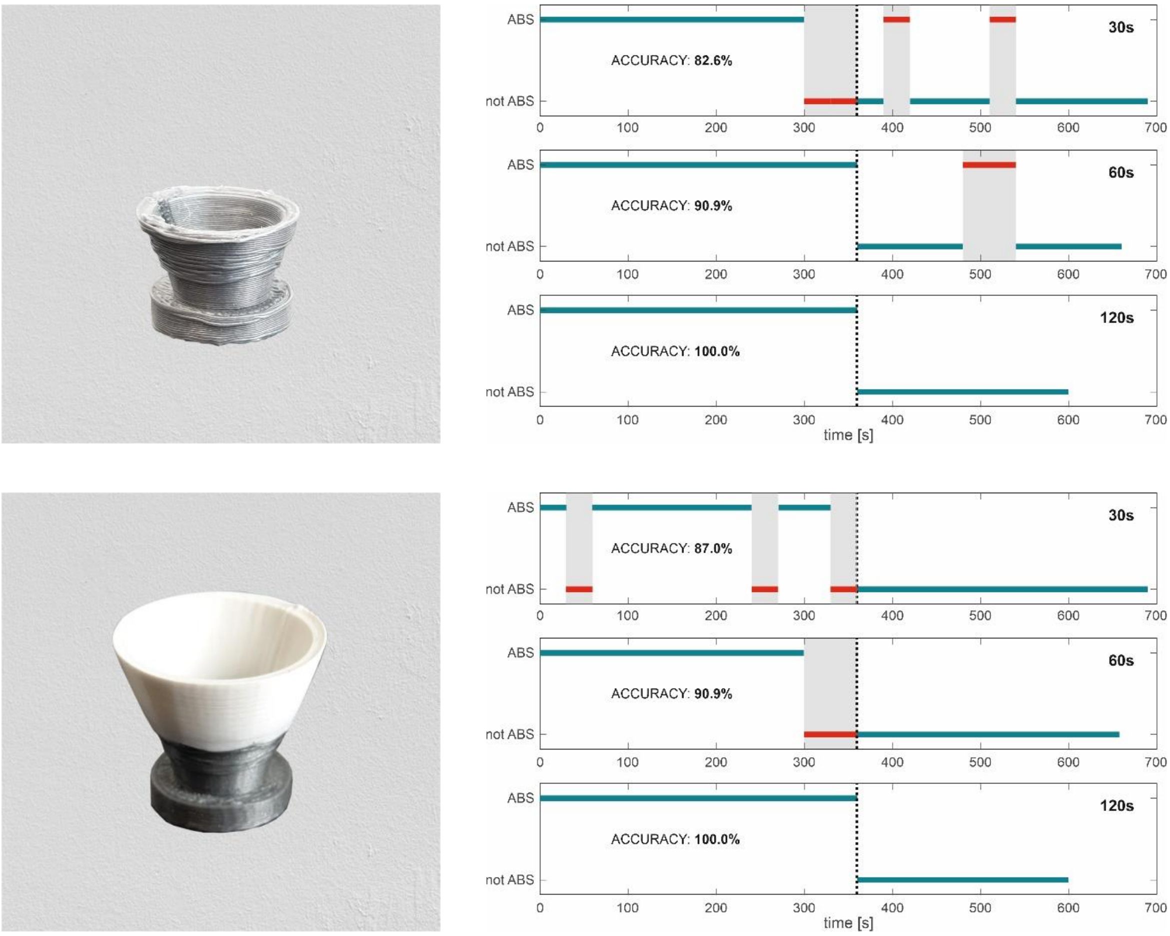

Figure 6. Automatic detection for two faulty samples: filament absent 6 minutes after the start (top row), ABS filament misplaced with PLA 6 minutes after the start (bottom row). Incorrectly detected segments are marked as shaded regions.

4. Discussion

The proposed method demonstrates its effectiveness by correctly indicating misused filament type common in fused filament fabrication parts with accuracy of 86.4%. The major advantage of this approach is that monitoring of the printing process can be performed in a simple, completely non-invasive way, without having any additional impact on the printing process. This system can be implemented for real-time control monitoring on the layer-basis by independently processing data acquired for a single layer and, as a result, issuing a warning if type of the filament has been changed during printing process.

The empirically obtained results presented in this report are preliminary and need further testing and improvements. Since the system requires pre-trained model, the sample size used for generating such model should be large enough and the system needs to be tested for different sample designs on different machines using more filament types. The information based on the knowledge derived from previously processed data segments as well as including data from extra sensors has been currently considered to be included into the system.

References

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