In Situ estimate of ultimate tensile strength for part optimization in extrusion-based additive manufacturing

Sadegh Nouri Gooshki¹, Fabian Hough, Damas W Limoge, Aswin Raghav Nirmaleswaran, Vadim Pinsky and Matthew Putman
Nanotronics, 63 Flushing Ave., Brooklyn, NY, USA 11205
1E-mail: sgooshki@nanotronics.co

Abstract. Uncertainty in the final mechanical characteristics of an extrusion-based additive manufacturing process is a major challenge for the field. Estimating these mechanical characteristics of the specimen during printing can save cost and resources, allowing for the application of optimization methods to correct for natural error. We propose a deep learning based computer vision approach to continuously estimate the tensile strength using recent images of each printed layer, and acting to critique the efficacy of the extrusion process. This predictive model is useful for in situ part optimization, maximizing the output prediction.

1. Introduction
Characterization of mechanical samples is a routine procedure in material sciences and engineering. Measurement of tensile strength, denoted as $t_s$, is used to inform additional properties like Young’s modulus, Poisson’s ratio, and strain-hardening characteristics [1]. For additive manufacturing, this is frequently the approach, with tensile testing used to characterize new materials [2] and structures [3]. Extrusion-based additive manufacturing, often referred to as fusion deposition modelling (FDM) or fused filament fabrication (FFF), are subject to variation of extrusion rates that cause voids [4], which result in variations of strength. For any manufacturing process, consistency is a key focus, and the minimization of variation in tensile strength in additive manufacturing continues to be a challenge. However, for algorithms that attempt to optimize this quality metric in situ, an estimate that requires completion of the part comes too late. For optimization algorithms intending to correct naturally occurring errors, an estimate considering the most recent print state is required.

Applications of deep learning to optimization schemes have been observing a steady growth in recent years, leaning heavily on the use of Deep Neural Networks (DNNs) [5]. This type of model can be used to optimize the trajectory of an agent through an environment, analogous to adjusting system parameters during a print to minimize variations. State of the art optimization requires a gradient to be established between each action, such that the policy changes as a function of the received reward [6]. This requires on-policy decisions to be made using rewards for each back-propagation iteration, ideally after each reward. The focus of this paper is on the in situ estimation of $t_s$ in an extrusion-based additive manufacturing environment to provide an optimization algorithm with a best estimate of the efficacy of an action. The construction and training of that optimization algorithm is outside the scope of this research and is the focus of on-going work. The purpose of this estimation is not to accurately predict the tensile strength of the final part, but to predict the apparent tensile strength given a subset of images. For features that are nominally average, the prediction should be average, while features that represent deviations from nominal should result in predictions that reflect that deviation.
Figure 1. A schematic of the part used for experimentation and validation of the estimation methods, with units in millimeters (The part resembles a 3D dogbone which has extended blocks for ease of gripping by a tensile tester: The smallest cross-sectional area is shown at Section A-A, while the specimen was gripped along the square dimension at the top; The center 100 layers are considered to be the layers of interest, shown in green on the image; Layers were printed at a thickness of 100 µm and 100% infill).

2. Method
The features of the proposed model require two distinct data streams: images of each layer printed and the tensile strength of the part after the print is complete. The printer was modified to take an image of each printed region for every layer, using photometric illumination vectors to minimize the variation of surface reflection. Figure 1 shows the tensile specimen used for this research. It is derivative of ISO 527-1 [7], but changes were made to better suit the design of the experiment. In the interest of having inter-layer fusion dominate the dynamics, the part was printed with its Z-axis parallel to the tensile strength, but ISO 527-1 proved difficult to print in volume with this orientation. An adjustment was made to increase the surface area of the first layer, and to confine the expected break in the region of interest, the center layers were also revolted. This had the additional benefit of eliminating the need for bridging support material. Figure 2 shows the tensile testing apparatus used for this experiment. To condition the tensile estimate further, an additional measurement was made of the location of the break layer with respect to the layers of interest.

Material characterization using machine learning has precedent, often in macro contexts such as construction concrete [8], graphite deposition in industrial settings [9], and for automatic characterization of powder beds in additive manufacturing [10]. Additionally, reward estimation schemes also exist in literature, such as for the reduction of stochastic corruption of reward signals [11] and the interpolation of discontinuous reward structures [12]. The novel contribution of this work is to combine both paradigms into a complete structure, enabling reinforcement learning based optimization in-process using state of the art techniques requiring dense reward structures. In Section 2.1, a brief discussion of the underlying mechanics is given, as well as the proposed mappings achieved by inferential networks and their respective loss functions. Section 2.2 describes the additional measurement made of the break layer, as well as the data flow from acquisition to model training.
Figure 2. The tensile test apparatus used for data acquisition (The sample frequency was 50Hz, with a travel speed of 0.5 inch/min; The maximum force limit of the gauge was 200 lbf, with a 0.1% resolution).

2.1. Model overview
A quality metric of interest in additive manufacturing is the strength of the printed part, which is anisotropic and dependent on the orientation of the part while printed. A predictive model was trained and validated by printing a specimen, shown in Figure 1, with its longest dimension parallel to the Z-axis of the printer.

The specimen was then pulled in tension, also parallel to this dimension, to determine the ultimate tensile strength, \( t_s \). The formulation of tensile strength is established by,

\[
\sigma(z) = \frac{F_a}{A_c(z)} \\
\epsilon(z) = \frac{\sigma(z)}{E} = \frac{F_a}{A_c(z)E} \\
t_s = \max \frac{F_a}{\sigma(z)}
\]

where \( F_a \) is the applied force, \( A_c \) is the cross-sectional area as a function of the axial dimension \( z \), \( \sigma \) is the tensile stress, \( \epsilon \) is the tensile strain, \( E \) is Young’s modulus for a given material, and the ultimate tensile strength, \( t_s \), is the maximum applied force while the specimen has not fractured. Tensile strength has been used previously for mechanical characterization of 3D print parts [13, 14], often focusing on infill raster orientation and using an applied force axis perpendicular to the printed Z-axis.

A non-linear function can approximate \( t_s \) for each layer, \( i \), from top-down images, \( I_i \), of the specimen. The images are transformed to feature vectors by an extraction network, defined as,

\[
f: I_i \to \hat{f}_i
\]

The estimation of tensile strength, \( \hat{t}_s \), from the feature vectors [15] of a window with length of \( m \) prior to the \( i^{th} \) layer, is formulated as a mapping, \( g \), given by,

\[
g: F_i \to \hat{t}_{s,i}
\]
where $F_i$ is a matrix of feature vectors defined as $F_i = [\vec{f}_{i-m+1}, \ldots, \vec{f}_i]$. To condition the estimation of $\hat{t}_{s,i}$, the break layer, $b$, was included in the output label, and Equation (3) can be rewritten as,

$$g: F_i \rightarrow [\hat{t}_{s,i}, \hat{b}_i]^T$$

where $\hat{b}_i$ is the prediction of the break layer for a feature matrix, $F_i$. The tensile strength estimation network, $g$, is trained by minimizing a loss, $\mathcal{L}_{t,k}$, for the $k^{th}$ tensile specimen,

$$\mathcal{L}_{t,k} = \frac{1}{n} \sum_{i=1}^{n} (\hat{t}_{s,i} - t_{s,k})^2$$

and the break layer, $\hat{b}_i$, of Equation (4) can be approximated by minimizing an independent loss, $\mathcal{L}_{b,k}$,

$$\mathcal{L}_{b,k} = \frac{1}{n} \sum_{i=1}^{n} (\hat{b}_i - b_k)^2$$

An attention block method [16] is used to encode the break layer, $b_k$, for an accurate estimation of $t_s$ using the most recent features of the specimen, $F_i$. The break layer, $b_k$, is a measured value using a designed algorithm, $C$, from lateral images taken along the perpendicular plane to the print surface.

**2.2. Data collection and prediction scheme**

An extrusion-based, open-source printer was chosen as the test bed, modified to have cameras mounted to the extrusion head, designed to not interfere with normal printing. Tensile strength, $t_{s,k}$, was used for each printed specimen as a label in training. Additional image acquisition was set up to capture lateral images of printed specimen at the macro scale after a pull test, to determine the index of the break layer, $b_k$. The print specimen consists of 500 layers, where the middle 100 layers, layers 200-299, were used as the layers of interest. Transverse layer images, showing the top of each layer, were taken after each layer with the mounted cameras. The lateral images were used to extract the layer count of each pulled half to estimate the break layer, while the transverse layer images were used to estimate $\hat{t}_{s,i}$. Figure 3 shows an overview of the system components. Figure 4 shows an example of lateral images after the tensile test.

![Figure 3](image-url)

**Figure 3.** (Left) Printing and imaging system components: As each layer was printed, the mounted cameras took an image; Once a specimen had completed printing, a tensile tester was used to measure $t_{s,k}$, and a lateral image was taken of the pulled specimen; (Right) Software system components: The collected lateral image was used to estimate the break layer, $\hat{b}_i$, to be used in conjunction with the collected $t_{s,k}$ as labels for $\hat{t}_{s,i}$; The input to the system was the features of collected layer images, $F_i$.

The proposed approach to estimate $t_{s,k}$ in situ for each print layer includes the following main software components: break layer measurement system and tensile strength estimation. A tuned computer vision algorithm, $C$, was developed to measure the break layer $b_k$ using the lateral image, $I_{l,k}$, for the $k^{th}$ specimen, given by,
The measured break layer $b_k$ is used as a conditioning label along with the measured $t_{s,k}$ for training the $\hat{t}_{s,i}$ estimator system. The layer count measurement algorithm used lateral images, $I_{l,k}$, as input. This algorithm identified the pulled pieces of the specimen in the image, pre-processing with a median blur, adaptive thresholding and dilation, then blob detection for segmentation [17, 18]. The number of layers in both segments were counted by second-order moments of the blobs, and the vertical length of the blobs were returned as a mapping from pixels to layer count. The layer count in both pieces were used to calculate the break layer, which was used as the label for Equation (4). A failure estimate of the algorithm was also returned, such that training would be conducted for specimen with high confidence of the break layer. The application of the algorithm is shown in Figure 4.

Figure 4. (Left) Lateral images of pulled specimens: (A) before analysis, (B) a successful measurement converted from pixel space to a discrete layer number; (Right) Tensile strength estimation system consisting of two branches: a GRU branch is the main branch and was trained on $t_{s,k}$ labels, and an attention branch which was trained on $b_k$ labels; The output culminates in fully-connected (FC) layers and a linear activation.

The tensile strength estimator module was fed by a matrix of feature vectors, $F_l$, extracted from transverse layer images, as input and was trained on a tensile strength label for the whole specimen, acquired through a tensile strength pull test. A model based on convolutional auto-encoders [19] was used for feature extraction from images, as expressed in Equation (2). The feature extraction model was designed in a way that encodes image and scalar data describing layer conditions into a single feature vector, in a multimodal [20] fashion. The tensile strength estimation system was built using a recurrent neural network (RNN) [21] by combining a gated recurrent unit (GRU) [22] and an attention block [16], with accompanying fully connected layers. Other studies have used GRUs for manufacturing applications, such as in wear and life-span prediction [23, 24].

The $\hat{t}_{s,i}$ estimator consists of two branches, as shown in Figure 4. These branches are the GRU branch and the attention branch. The GRU branch was trained on $t_{s,k}$ labels from the pull test while the attention branch was trained on break layer labels generated by the break layer measurement system. The parameters of the attention branch were optimized independently, while the output of attention block affected the GRU branch since it was applied on the GRU output by element-wise multiplication. The tensile estimator was trained with a time step, $m$, where $m$ layers were used to estimate the tensile strength for the $i^{th}$ layer. Hence, the $\hat{t}_{s,i}$ values were only estimated for the $m^{th}$ layer and all subsequent layers. Both branches were trained on a continuous value spectrum as regressors. The purpose was to estimate the $t_{s,k}$ value for each layer, $i$, in such a way that the model can predict a lower $\hat{t}_{s,i}$ values for weak layers and the break layer, compared to normal and strong layers.
3. Tensile estimation results

The performance of the break layer measurement system was quantified for its ability to catch failure cases in layer counting. The train and test sets were split in a 9:1 ratio and a K-fold approach was used for parameter tuning of the break layer estimate, resulting in a 96% validation accuracy. The measurement system was then used to create the break layer estimates for the 2562 specimens used for the tensile estimator. To train the tensile estimator, 2292 specimens were used for training, and the trained model was validated on 270 specimens. A typical result is shown in Figure 5, where weakened layers result in lower estimates, while apparently strong layers result in higher estimates. The tensile estimator model was trained and evaluated with a time step of \( m = 10 \).

Figure 6 shows the complete results, plotting a histogram of normalized deviations. These deviations are calculated between estimated \( \hat{\ell}_{s,l} \) against true \( t_{s,k} \) for all validation samples. The layers with a lower estimated \( \hat{\ell}_{s,l} \) can be interpreted as weak layers, whereas layers with a higher estimated \( \hat{\ell}_{s,l} \) value can be interpreted as normal or strong layers. The overall validation mean absolute percentage error for estimating the neighborhood average, \( b_k \pm 5, \hat{\ell}_{s,l} \) at all break layers is around...
42.02%. The average error for the estimation of the neighborhood average $\hat{s}_i$ at the break layer in the validation set is 29.84 lbf. These results are difficult to validate further through conventional means, as the goal is not to minimize error for every feature vector explicitly. Instead, the best validation metric is the optimization validation obtained by using this system. This is on-going work, and will be published in future literature, while the structure of that optimization is outside the scope of this paper.

4. Conclusions

In situ characterization of extrusion-based additive manufacturing parts is enabled by state of the art applications of feature extraction, state-memory prediction models such as a GRU block, and output conditioning using computer vision estimation of meta features such as break layer. While tools that are able to make predictions from a completed process are valuable, in-process adjustment requires predictions that critique the most recent state information available. The system presented here is capable of providing that immediate reward signal, to be optimized by a learned policy.

The proposed approach provides a model that can be deployed on printer hardware leveraging a layer-wise image acquisition system, providing critiques of the extrusion as correlated to tensile strength. This prediction is a rolling estimation of the quality of the printed part and is being used to validate optimization algorithms for minimizing deviations within the additive manufacturing process as future research. While Figure 5 shows a type of validation, the only true validation is using this system in-line with an optimization scheme, currently undergoing tests with a proximal policy optimizing agent. The future validation will be affirmed by the optimization of this agent with respect to this prediction scheme. This type of non-destructive characterization is essential for the wider adoption of additive manufacturing in industries that rely on predictability of manufacturing and consistency of system output.

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