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IDENTIFY PRINT QUALITY OR SUB-SYSTEM DEGRADATION ISSUES FOR 3D PRINTERS USING LAYER TIME ANALYSIS

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Identify Print quality or Sub-system degradation issues for 3D Printers using Layer Time analysis

1. Abstract

One of the core concepts in additive manufacturing is to have accurate powder deposition on bed with uniform duration throughout the print job. The inaccuracy in job layer duration arising when some layers take more or lesser than the recommended value, often results in bad part quality issue or indicate issues with print hardware components.

This disclosure describes a method for improving Print Quality (PQ) and reduce unplanned downtime (due to sub-system failure) by looking at layer time for the print cycles and figuring if they are running off the prescribed limits for the material used. Based on this information the erroneous machines can be inspected for diagnosing fault. Analysis by services and support (using the information from the cases flagged using this technique) suggests the dominating cause to be hard drive failures (replacing which solves the problem), though there can be other reasons as well.

2. Problems Solved by Invention

Some 3D printer use additive manufacturing as a digital technology to create objects by adding several deposits of layer stacked on top of each other. One of the biggest challenges with the additive manufacturing is how to control the manufacturing output quality and achieve consistent results. Another issue is the system reliability, keeping the manufacturing devices up and running, minimizing unplanned downtime. This work contributes to improving both by using analysis of the layer time and shows how the information is currently used (in ad hoc way) and plans to incorporate this into a shipped product.

Analysis of the jobs from 3D Printers with unsatisfactory part quality or unplanned downtime suggests that one of the causes can be traced to hardware sub-system failure (HDD failure etc.). It turns out that checking for the consistency in print layers can unravel information about these failures prior to having potentially catastrophic impact (sub-system failure) and increase in systematic degradation of part quality (PQ).

The duration of print layer depends upon multiple factors – HDD health, powder movement through the internal sub-component at the precise time and uniform layer deposition on the print bed across the job. An inconsistency in the layer timing can lead to (or could be affected by) bad HW health and / or undesired part properties. Existing system mechanism does not trigger any alert or system event when the layer duration goes exceedingly long and effects system’s health and hence the problem occurring due to layer duration anomaly largely goes unnoticed. This predictive model helps determine whether a significant proportion of layers deviate from the recommended threshold of the layer duration and thereby indicate that powder deposition was not uniform. An alert on this would help take corrective action by the customer (often replacing the faulty hard-drive) or to be able to associate bad part quality with the reason.

3. Prior Solution and Challenges

Prior solution in place by Customer Assurance and R&D team has used simple descriptive statistics measures on Layer duration and used naïve heuristic constant (Kurtosis of layer duration > 3) as an indicator of bad HDD quality. However, this appears to be a crude solution as the Kurtosis value around 3 assumes the layer time to follow Normal distribution which is not always the case. Also, this was not a predictive solution and used to be performed as a post mortem analysis once HDD failure was reported.

4. Description of Invention

The objective of the analysis is to determine two things; firstly, do layer durations follow the same pattern throughout or how many distinct layer patterns are found and secondly, what percentage of layers take abnormally long or short time to finish. The proposal thus presents using Gaussian Mixture Model with Jensen-Shannon divergence criteria as a measure of component selection and uses a custom algorithm to detects outliers (abnormal layer duration) in the print job.

a. Background

In Statistics, a mixture model is a probabilistic model that defines presence of sub-population in an overall population. Gaussian Mixture Model (GMM) is a type of mixture model that assumes underlying sub-populations to follow Normal probability distribution. However, since no prior knowledge of sub-population is required, this algorithm is unsupervised in nature. Theoretically, for multimodal data (i.e. the histogram shows more than 1 peak), Gaussian Mixture Models are often the most suitable choices.

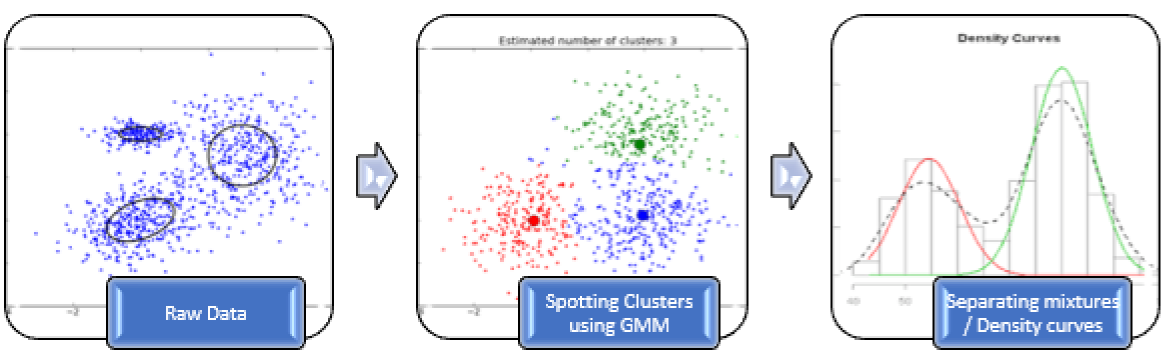

Figure 1. Using GMM model to visualize Layer duration behavior

The Gaussian Mixture Model has two parameters; the mixture component weights (i.e. the probability of a data element to belong to each of the sub population) and secondly, the component means and variances (for each of the underlying sub population). A simple one – dimensional GMM with k components has following probability distribution function:

$$f(x) = \sum_{i=1}^{k} \phi_i N(x_i|\mu_i, \sigma_i)$$

Where ɸi is component weight, telling the probability of a data row to belong to ith mixture and each mixture is normally distributed with mean μi and variance σ2i as follows:

$$N(x|\mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} exp\left(\frac{-(x - \mu)^2}{2\sigma^2}\right)$$

The parameters are estimated by using expectation – minimization algorithm.

As the model is unsupervised, the key is to choose the optimal value of k or number of mixture components present in the data. There are several methods available in theory such as:

- Fit multiple models with varying values of k and estimate the BIC (Bayesian Information Criterion) score and choose the model with lowest BIC.
- Fit multiple models and choose the one with lowest value of AIC (Akaike Information Criterion)
- Use cluster performance indicators like Silhouette score and choose the model with highest silhouette score

Different techniques could yield different value of k. However, the techniques mentioned above have their own merits and demerits and often do not save use from overfitting the data.

The invention proposes using Jensen-Shannon divergence criteria as a robust measure for component selection. Jensen-Shannon provides a smooth and symmetric version of Kullback–Leibler divergence and computes a score to measure how two probabilistic models are deviating from each other. Lower the divergence score, higher is the agreement between the models to fit the data.

In our case, each dataset of print layers, is equally and randomly split into two halves for training and testing purpose. Both train and test datasets are run with the same number of clusters and the divergence score is computed as follows:

$$JS\ (P||Q) = 0.5 * (\ KL(P||M) + KL(M||Q))$$

Where:

KL(P||Q) is the KL divergence between the two probability distributions – P and Q over the same space and

M = 0.5 (P + Q) to make the divergence symmetric. KL divergence between the two probabilistic distributions over the same space is defined as follow:

$$KL(P||Q) = \int_{-\infty}^{\infty} p(x) * \log(\frac{p(x)}{q(x)})dx$$

The best cluster solution is the one where training and test data have lowest J-S divergence.

b. Proposal

The job payload in 3D MJF printer provides several different measures of the layers that should be printed when a job completes successfully. A print job comprises of several types of layers, starting from warming-up phase with design and warming up layers and continues until the end of annealing phase. Figure 2 provides a schematic diagram of layer stack in a print job.

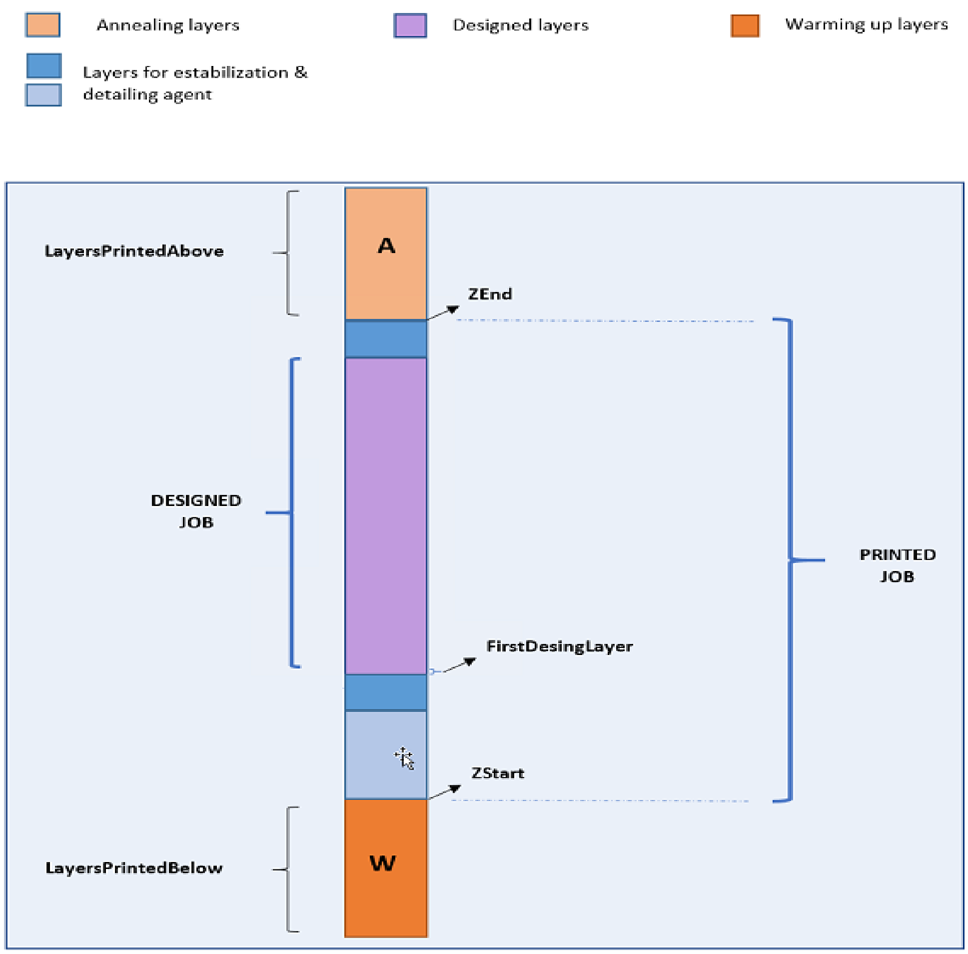

Figure 2. Job Layer Distribution

The proposed solution focuses only on the layers taking place during Print phase (Printed Job layers) as they largely govern the overall part quality as well as the printer subsystems' heath during a job.

The invention suggests involves following steps:

- Extract layer duration in milli-seconds from Printer.log for each job. The job.xml payload currently parses layer duration in seconds precision and is not sufficient to carry out the analysis and assess the layer health. A solution to this is to directly parse printer.log raw file and write to a table to analyze layer duration against its index. Once the data parsing is completed, a univariate GMM model is applied on this table that consists of layer index and duration captured in milli-seconds. Figure 3 represents a schematic diagram of the system architecture behind the parsing.

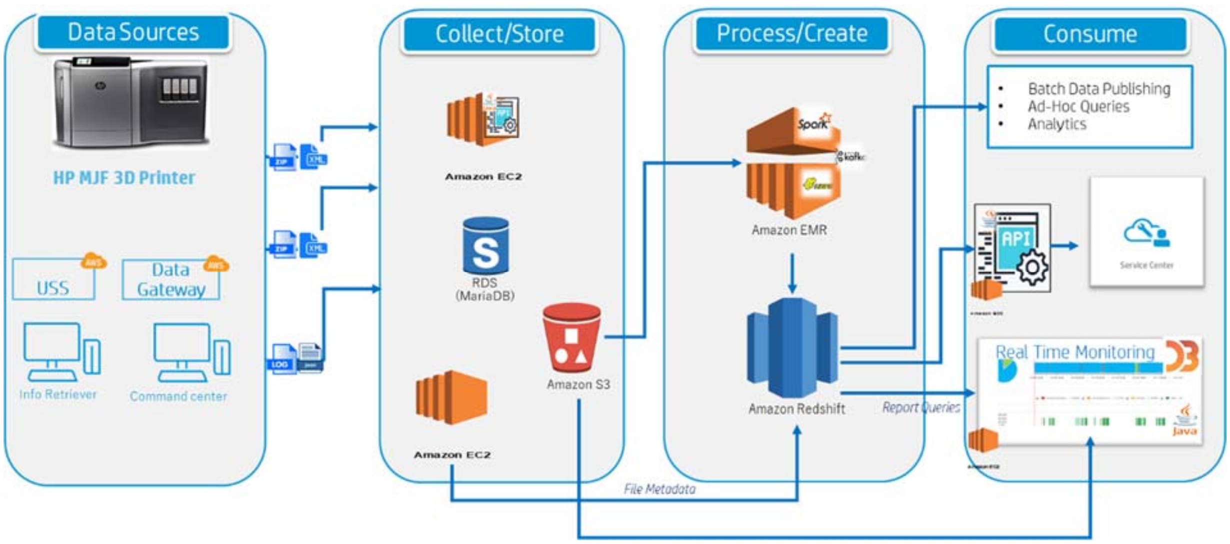

Figure 3. System Architecture Diagram

- Subject the data to GMM model with a grid of all possible models ranging from 1 to 10 different components, for each possible covariance types – full, spherical, tied & diagonal and compute Jensen – Shannon distance for each model.

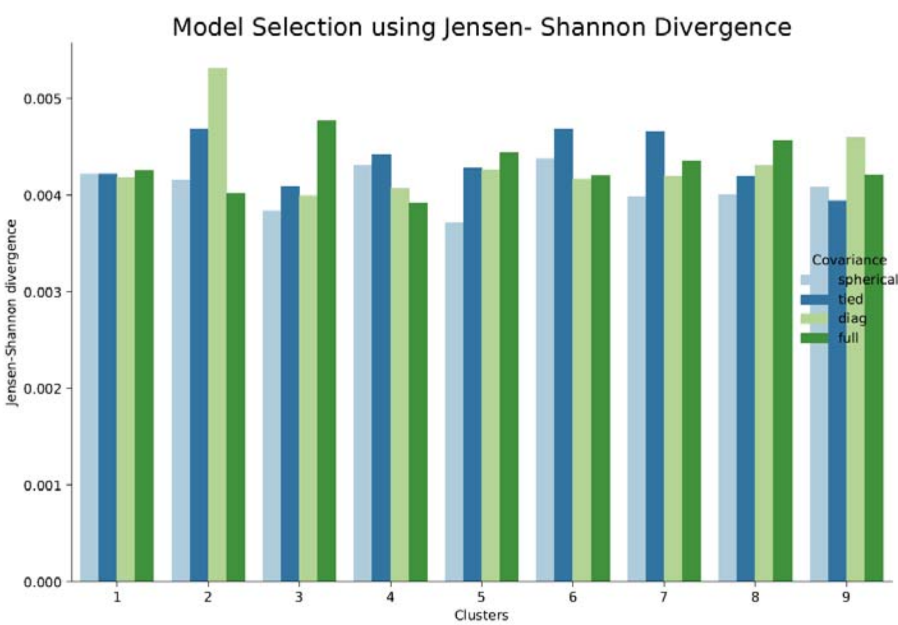

Figure 4. Model selection based on J-S distance

- Select the model with lowest J-S distance. This would provide different types of distinct layer behavior during print job. Layer behavior can also be plotted for visual analysis. Although, in reality, a unimodal distribution (ideal layer duration behavior) rarely occurs, however, an acceptable layer duration should be largely governed by single process with mean as defined in the baseline thresholds. There have been numerous occurrences of layer duration showing bimodal graph (i.e. having two distinct layer behavior, possibly a delay in recoater-scan axis movements) or even multimodal graph implying that layer durations are not uniform leading to part quality issues. Figure 5 shows an example of 3 different jobs run on the same customer machine at different time periods.

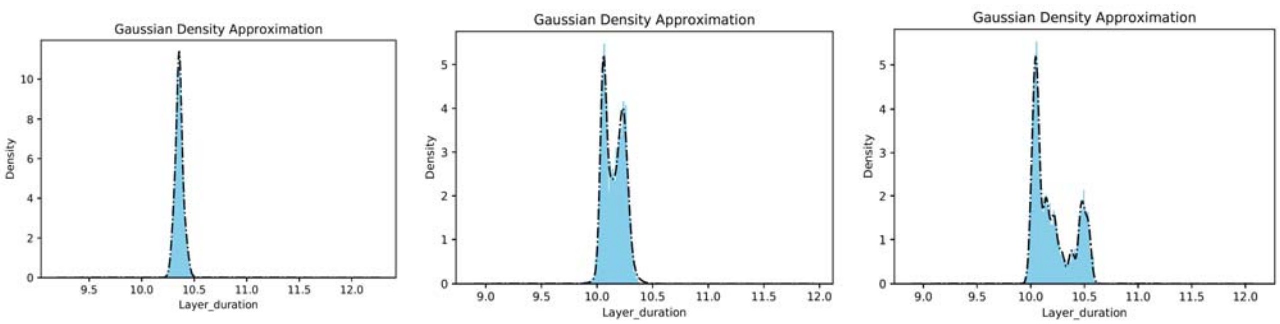

Figure 5. Types of layer behavior

- To determine the outliers, provide the baseline threshold of layer duration to the specific combination of print mode and material being used. To compute these baseline thresholds, the GMM model was run over 3000 different print jobs and estimates are as follows:

	Polyamide 12	**Polyamide 11**	**Polyamide 12(Glass beads)**	**Polyamide 12 (Other)**	**TPU (open)**	**TPU (Lubrizol)**	**TPU(BASF)**
Balanced	11.00 sec	10.12 sec	14.00 sec	11.00 sec	14.44 sec	19.05 sec	14.23 sec
Cosmetic	11.00 sec	10.12 sec	NA	NA	NA	NA	NA
Fast	7.56 sec	7.56 sec	NA	NA	NA	16.97	NA
Mechanical	11.00 sec	11.00 sec	NA	NA	NA	NA	NA

- From the GMM model, compute the density of each mixture region and check the deviation (GMM Outlier percent) from the baseline threshold, for given print mode and material.

- Layer duration health is to be assigned based on following criteria:
  - *GMM Outlier Percent < 0.01 →* ***Ok***
  - *0.01 ≤ GMM Outlier Percent ≤ 0.02 →* ***Moderate***
  - *0.02 < GMM Outlier Percent ≤ 0.04 →* ***Bad***
  - *GMM Outlier Percent > 0.04 →* ***Needs Action***

Figure 6 shows an example of *bad* layer behavior as spotted in the outlier representation.

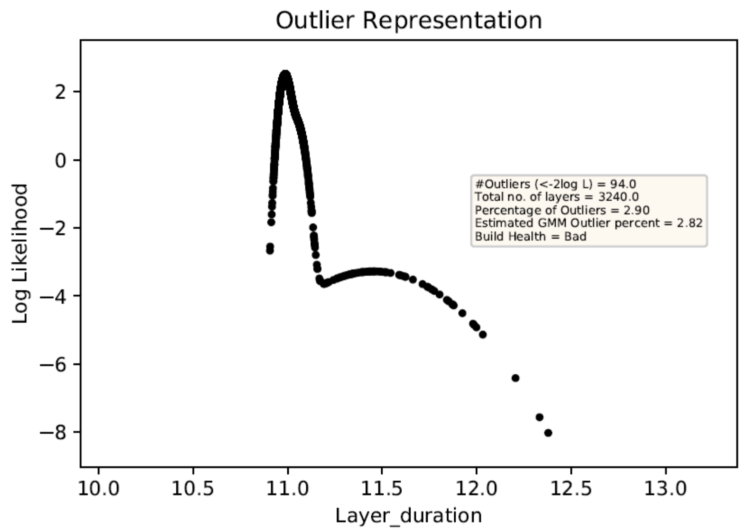

Figure 6. Outlier representation

c. Advantages

Prior solution in place by R&D and Customer Assurance was based on simple heuristics and moreover was used as post-mortem analysis and hence was not a predictive solution, for Hard drive failures. The process and system described in this disclosure that uses Gaussian Mixture Model with Jensen-Shannon divergence criteria

has used simple descriptive statistics of the layer duration and used naïve heuristic constant (kurtosis of layer duration > 3) as an indicator of the bad layer quality. However, this was not a predictive solution and was carried out as post reporting analysis on instances of hard-drive failure by the customer.

The process and system described in this disclosure (that uses Gaussian mixture model with Jensen-Shannon Distance as a measure of component selection for outlier detection) is

- more robust (across the install base and different time periods)
- correctly predicts ahead (in many instances as much as several months before) instances of issues (stemming from hard-drive failures in several cases, based on data from the field), improving up-time for the machine and preventing issues that lead to poor PQ (part quality)

The model is going to be deployed in internal predictive maintenance tool for our quality and support teams to preemptively engage with customers potentially saving warrant costs and unplanned downtime. Further, we are also working with the Productivity Monitoring Suite of applications to allow our customers to be aware of these issues and proactively seek support engagement to preempt PQ and subsystem failure risk, resulting in planned maintenance and consistent PQ (part quality) by mitigating one cause for such issues. There is also a discussion about baking this into an alert generated on-device telemetry data, that would enable use cases for real-time action (canceling the job) as well as on-premises consumption.

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