Image treatment of spatter flight phenomena for porous metallic parts using powder bed fusion

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KEYWORDS: Powder Bed Fusion, Porosity, Spatter, Particle, High-Speed Imaging, Image Treatment, Prediction

The Powder Bed Fusion (PBF) 3D printing method introduces porosity into the final structure of the printed part. It is necessary to be able to predict the percentage porosity when different percentages may be acceptable or desired. To do this, an image treatment method using high-speed imaging was developed to obtain feature values as the part is constructed. This method breaks down the image such that only the prominent features, mainly the spatter, are visible. Noise is then removed from the image and the feature values are isolated and quantified. The program can output a variety of feature values including spatter and particle count, and ejection angle. Some feature values are summed, such as the spatter and particle counts, and some are averaged such as the ejection angle. These feature values are then used to predict the porosity via a least absolute shrinkage and selection operator (LASSO) model. Image treatment of the highspeed video has proven successful and the noise is able to be managed such that a useful number of particles can be analyzed.

NOMENCLATURE

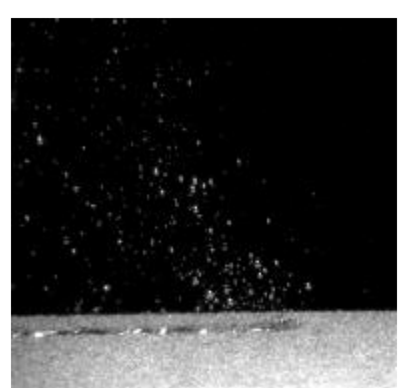
PBF = Powder bed fusion
LASSO = Least Absolute Shrinkage and Selection Operator

1. Introduction

Powder Bed Fusion (PBF) is a 3D printing process in which powdered metal is fused together through the use of a laser to produce an object. The physics of this process are well understood but complex and thus the physical properties of a printed part can vary greatly under different production conditions. Observations of the molten pool and the fusion of the powder can be difficult to capture due to interference from the laser and the relatively small area over which the melt pool forms. Thus, it was decided to observe secondary effects of the PBF process in an attempt to determine the physical properties of the fused powder. The primary target of observation is the particles of melted, partially melted, and unmelted powder that are ejected from the bed as the laser moves across it.

These ejected particles display a variety of observable traits including the number of each type of particle, the velocity they move at, the angle they are ejected at, and their temperature. These traits vary depending on the scan speed and the power of the laser and can be used as additional data to help determine the final properties of the print. A highspeed camera and laser illumination system were set up to capture video of the laser moving along the powder bed. The video is then analyzed to find the particle traits, a frame of this video is shown in Figure 1 below. Quantifying the particle traits in these observations has proven to be difficult to do by hand as there can be a large number of particles in a single frame. In order to increase the accuracy of the particle counting and the consistency with which the observed traits are analyzed, a computer program is implemented. This program uses a form of machine vision to find, classify, and analyze the particles and is the subject of this paper.

Fig 1. Frame from high-speed video



The image treatment program is built using Python and primarily relies on Numpy and OpenCV to perform the computer vision tasks.

2. Methods

2.1 Particle Isolation

The first part of the machine vision process is to separate the particles from the background of the image. This is accomplished by making two comparisons. The first frame of the video when no particles are present is used as a clean plate to compare the remaining frames too; this is shown in Figure 2a.

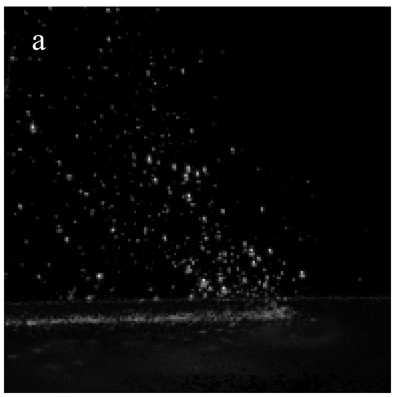


Fig 2a. Comparison of current and first frame

Due to noise in the background and the particles being filmed against the powder bed and not a clean background, the accuracy of only using a clean plate decreases as the video progresses. Thus, the clean plate method is supplemented by also comparing the current frame with the previous frame. This comparison yields a frame with less noise, but it doubles the number of particles due to how OpenCV handles the comparison as shown in Figure 2b. To fix this, the clean plate comparison is combined with the previous frame comparison to yield a frame with less noise and no doubling of the particles. The final result of this isolation is shown in Figure 3.

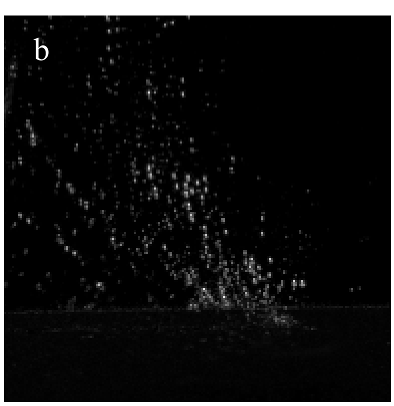


Fig 2b. Comparison of current and previous frame

2.2 Large Particle Counting

Once a frame containing only particles is found it can begin to be analyzed. This is first done by having the program look for contours which are found by comparing the particle colors. For the black and white images coming from the comparisons, finding contours looks for where the pixel changes from white (a particle) to black and defines that as a possible contour. The issue that occurs with this method is that large particles tend to overlap with other particles and an accurate quantification and analysis cannot be done.

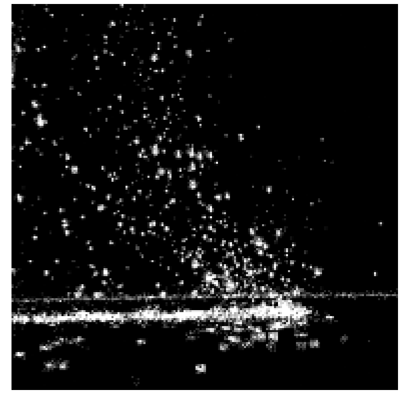


Fig 3. Isolated particles and noise

To fix this, a method for iteratively shrinking the large particles was developed. This is called disintegration and it involves reducing the size of all particles in the frame until the iteration limit is reached or all particles disappear from the frame. The method begins with the frame resulting from the comparison, shown in Figure 3. The contours from this frame are stored for comparison later. The frame is then disintegrated by one iteration reducing the size of all particles in the frame by roughly one pixel around their circumference as shown in Figure 4. The blue boxes are the original bounding contours of the particles, and the dotted lines represent the original shape of the particles.

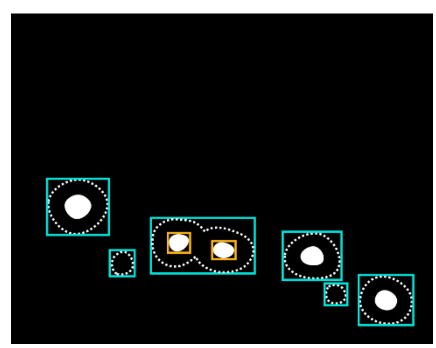
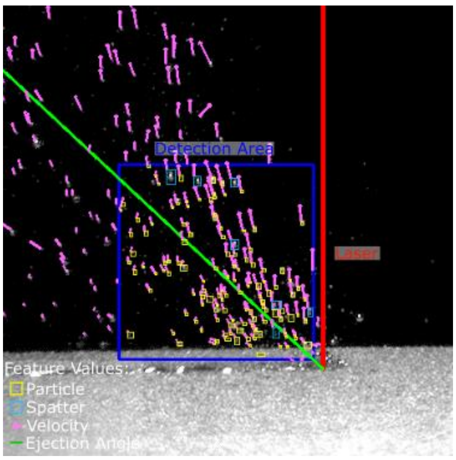


Fig 4. Diagram of Disintegration Process

The contours for this frame are then collected and a check is done to see if they lie within the original contours. If they do, then the original is updated to the new contour. This process then iterates. After enough iterations are performed, the particles shown as solid white areas are identified as separate particles and the orange bounding contours are set to save their positions. The goal is to see if a single large contour breaks into smaller contours as the particles are disintegrated. Once the iteration finishes the final list of contours is multiplied by the respective iteration number to return them to their original size. The result is that the overlapping particles are able to be counted individually.

2.3 Data Extraction

With the contours of the particles successfully found, the data collection can begin. The first piece of data to collect is the size of each of the particles which is considered to be the size of the bounding box that surrounds the particle, the contour. This ejection angle of the particles is also found. The center of each particle is found and then these coordinates are averaged in order to produce the ejection angle. The final contours can also be used as a mask with which to recover only the particles from the original image. Here the color of the particles can be analyzed in order to give a relative temperature or to



further distinguish between types of particles. A final frame with various data is shown in Figure 5. Once the desired data has been collected it is exported for use in the subsequent LASSO analysis.

Fig 5. Final image. Particle bounds and other information displayed over the original frame

3. Conclusions

3.1 Current Version

This computer vision method is able to find and classify particles with greater accuracy than the previous method. The noise in the individual frames was able to be reduced and more particles were found closer to the laser melt pool. This proved difficult before as the melt pool would leave a long trail in the comparison images that would make finding particles difficult. The data extracted from the program is able to be used with little formatting in a LASSO program to determine material properties. Examples of the type of data exported from the program are shown in Figures 6a and 6b.

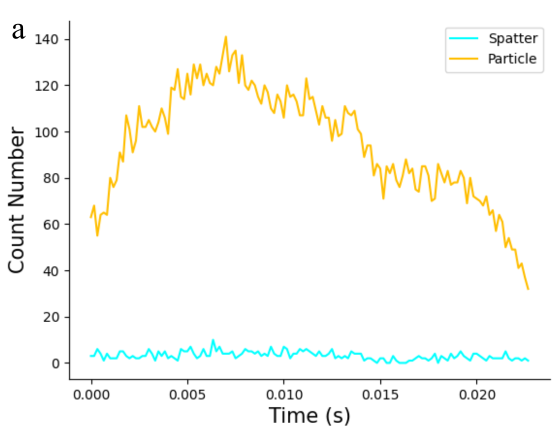


Fig 6a. The number of particles and spatter in each frame

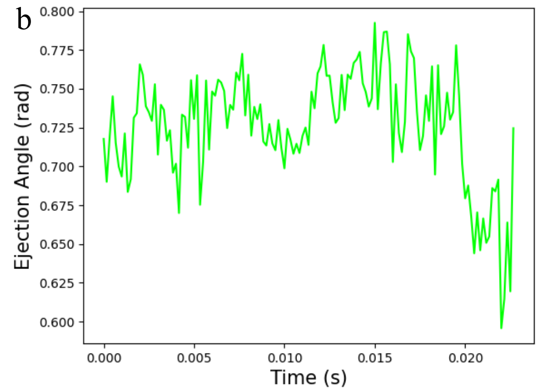


Fig 6b. The ejection angle of all particles in each frame

The clarity of the final particle clean plate allows for a good range of parameters to be found, including count, velocity, and color. From here it is possible to include other functionality in the code. Different methods for detecting and classifying the particles are possible, from the original rectangular sample region method to a radial method. Both can use the same image treatment process to achieve a clear view of the particles.

3.2 Future Work

This computer vision method is continuing to be improved as issues of dust and smoke have added additional noise that confuses the program into finding more particles than really exist. Further improvements to noise reduction in the area of the melt pool will help to find particles as they are created and further improve accuracy. Similarly, a reduction in the noise generated by the weld-line will help to remove possible misses.

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