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SHORT COMMUNICATION

Predicting gas pores from photodiode measurements in laser powder bed fusion builds

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Abstract

Recent studies in additive manufacturing (AM) monitoring techniques have focussed on the identification of defects using in situ monitoring sensor systems, with the aim of improving overall AM part quality. Much work has focussed on the use of of camera-based monitoring systems; however, limitations such as the slow response rates of the sensors (1-10kHz) and the post-processing requirements of the collected images make it difficult to apply these developmental monitoring methods on production systems in real-time. Furthermore, the replication of results from camera-based monitoring systems (often obtained using deep learning models) in a production environment is limited by the need for specialised hardware with high computational capacity (e.g GPUs). Focussing specifically on laser powder bed fusion (PBF-L/M), photodiodes, with fast data collection rates (50–100kHz) and providing data that is relatively easy to process are potentially better suited to real-time monitoring systems. The current study, therefore, focuses on using data collected from photodiodes to identify defects in PBF-L/M builds. A predictive model with real-time potential is proposed that, having been validated on data from computer tomography (CT) images, can be used to locate porosity within layers of PBF-L/M builds.

Keywords Laser powder bed fusion · Real-time defect detection · Time-series modelling · Autoregressive model

1 Introduction

Numerous process parameter combinations could lead to the generation of defects during the build [9, 13] , therefore, to produce high-quality parts, part quality needs to be monitored during the PBF-L/M build process. The level of porosity influences part quality indicators such as fatigue performance and crack growth characteristics of metal parts [5] and, as a result, porosity has received significant attention in the literature related to PBF-L/M [7, 10, 12]. This study also focuses on identifying porosity, especially gas pores, within parts built using PBF-L/M.

The proposed approach utilises a time-series model that aims to predict the value of future photodiode measurements. The underlying hypothesis of this study is that the difference between predicted and observed photodiode measurements could be used to infer regions of porosity. Interestingly, it was found that the model predictions were more accurate in regions of build porosity; with the rationale behind this, perhaps counter-intuitive observation is explained in subsequent paragraphs. Despite the counter-intuitive nature of our findings, the model was able to successfully predict the onset of porosity that occurred during 'standard operation' (in other words, the current study goes beyond simply detecting porosity that has been deliberately introduced through the variation of PBF-L/M process parameters [1, 4, 6, 11] . We note that, for the interested reader, further details behind this study are detailed in the thesis [8].

2 Model

Various time-series modelling techniques (e.g. auto-regressive (AR), moving average (MA), auto-regressive moving average (ARMA)) were initially considered as candidate model structures and assessed to identify the best structure. After verifying signal stationarity of the analysed photodiode signal by reviewing summary statistics and conducting statistical tests (e.g the augmented Dickey–Fuller test), the

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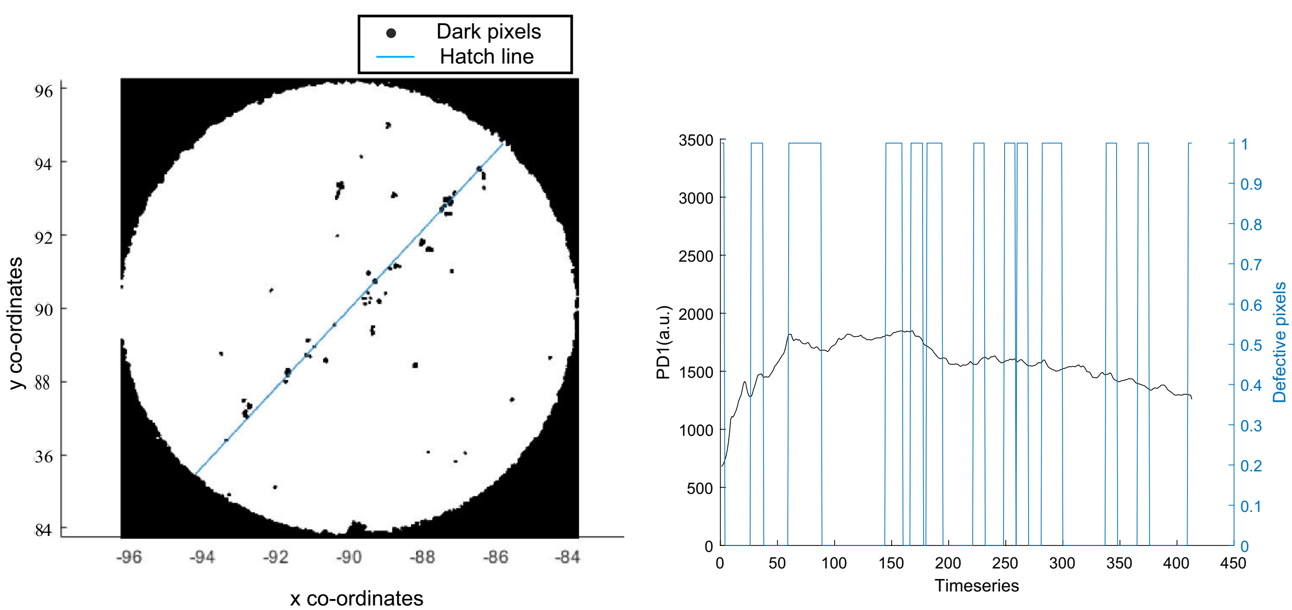
partial correlation of lagged components was observed in the graphs obtained from a partial auto-correlation function (PACF) analysis. The partial correlation of lagged components significantly dropped after the first two components. If the signals were suitable to be modelled by MA or ARMA, a gradual decrease would have been observed in the partial correlation of lagged components [2]. Since such a behaviour was not observed in the photodiode signals, an AR model was chosen to generate predictions of photodiode measurements. According to the results of a PACF analysis, more complex models with a relatively higher order (e.g 5, 50, 100) were incapable of making more accurate predictions; therefore, a second-order model was selected.

The model was trained on a photodiode signal (capturing melt-pool reflections in the 300–1000 nm wavelength range), of approximately 400 training data points. The model weighting coefficients were first estimated using a photodiode signal collected on a non-defective hatch line, though further experiments were also conducted whereby the model was trained on defective hatch lines (i.e. those which were later found to have resulted in porous regions); see [8] for additional details.

The vast majority of available studies are limited to the cases where defects are artificially induced by altering process parameters (e.g. [1, 6]). Such approaches may, however, provide poor representations of real defects, i.e. those that can still occur despite tuned build conditions and process parameters. To overcome this limitation, the current study analyses data collected during the fabrication of an PBF-L/M build, in which defects (captured via a CT image shown in Fig. 1 (a)) are naturally formed as a result of parallel fabrication of parts placed in a row with multiple laser beams.

A Bayesian approach for parameter estimation was adopted, whereby prior probability distributions over the model parameters are combined with a Gaussian likelihood function such that a posterior distribution over the weighting coefficients and likelihood variance ($\boldsymbol{w}$ and σ^2) can be realised. This approach allows us to quantify the uncertainty associated with our parameter estimates [3].

After training, the model was validated on signals collected from defective and non-defective hatch lines. The predictive error was then calculated by taking the absolute value between predicted and measured photodiode readings. An averaged predictive error, $\bar{e}_p(t)$, was then calculated using a sliding window of multiple readings (20 readings) belonging to the same hatch line and centred on the photodiode reading under consideration. The quantity $\bar{e}_p(t)$ was calculated to provide a measure of predictive error that is smoothed over a time window. This step has been added to improve the accuracy of the prediction, since the state of a melt-pool can be correlated with the state of the both prior and post melt-pools.



(a) (b)

Fig. 1 **a** A hatch line which passes through defective regions with dark pixel values (grayscale < 80) identified on a CT image. **b** Corresponding photodiode signal behaviour where blue line indicates, 1–defective and 0–non-defective

3 Results and discussion

The average predictive error, $\bar{e}_p(t)$, collected on Layer 42 of the PBF-L/M built part being considered, is plotted on the corresponding position co-ordinates in Fig. 2(a) to show an example of the results that were obtained. It can be seen that $\bar{e}_p(t)$ values below 20 often appear to be in regions that have been identified as defective via the CT scan (Figure 2(b)). We note that this is perhaps an unexpected outcome, as it indicates that the proposed model predictions are more accurate in regions of porosity.

In general, the proposed predictive model was found to be capable of predicting gas pores, with a minimum diameter of approximately 100 μm, with an average true positive rate (TPR) of 88.47%. Although the capability of predicting non-porous regions is slightly lower, 76.89%, on a layer where pores are not visible, the true negative rate (TNR) is 99.84%.

To understand these perhaps counter-intuitive results, we first note that, to the best of the authors' understanding, the photodiode signals relating to the porosity present were collected when a gas bubble was present on the powder bed. We hypothesise that this gas bubble has, in essence, acted as a filter, smoothing the signal and removing noise from the resulting photodiode measurements (and increasing their predictability as a result). To further investigate this hypothesise, we independently trained the model on hatch lines where porosity was later detected, and hatch lines where no significant porosity was detected. Figure 3 shows the posterior probability of the likelihood noise variance for these two cases, showing that the estimated noise variance for the defective hatch line is less than that of the

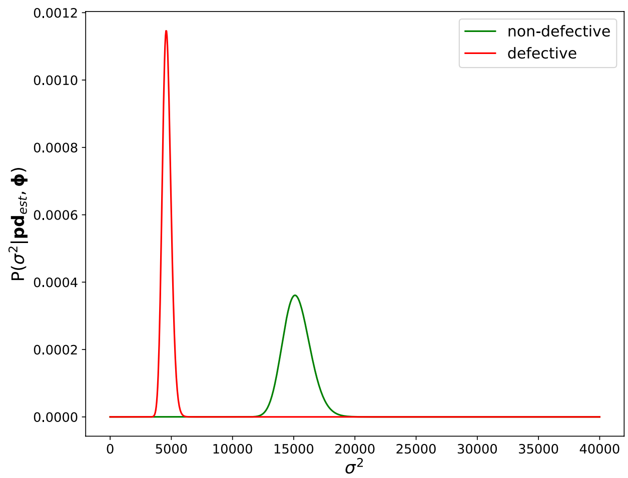


Fig. 3 The posterior probability distribution over σ^2 inferred from data relating to a defective hatch line (red) and a non-defective hatch line (green)

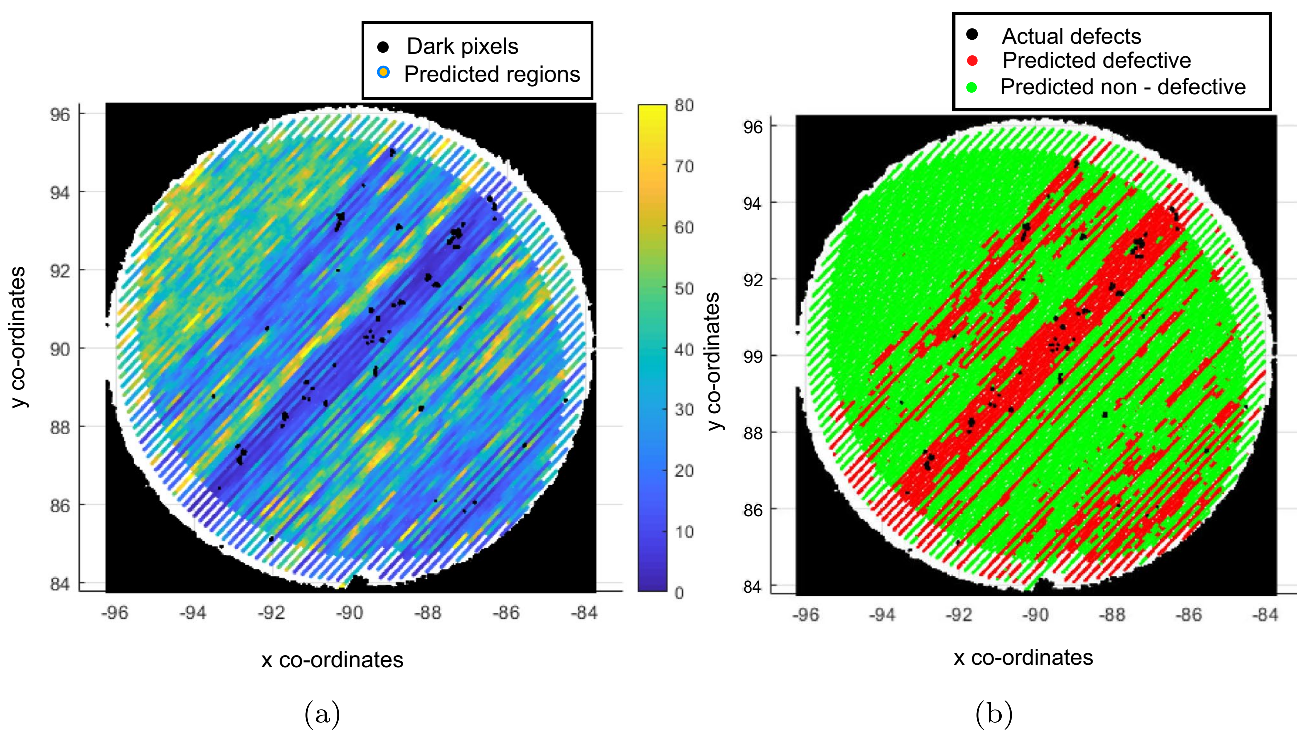


Fig. 2 **a** $\bar{e}_p(t)$ calculated along the hatch lines of layer 42. The defective regions of the corresponding CT image, with a gray scale value less than 80, are shown in black. **b** $\bar{e}_p(t)$ less than 20 are indicated in red, whilst $\bar{e}_p(t)$ higher than 20 are indicated in green

non-defective hatch line. Whilst this lends weight to our hypothesis, the authors accept this is not a definitive explanation as to why the proposed model is more accurate in regions of porosity. The approach, however, does appear to work well.

Fundamentally, it appears that, for the build investigated here, the onset of porosity has led to a change in the structure of the resulting time-series photodiode data. The ability of more complex time-series modelling approaches to improve predictive accuracy and/or reveal more about the relationship between photodiode time histories and the onset of porosity in PBF-L/M builds is currently a topic of ongoing work.

Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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