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| **Knowledge Exchange – Project Report** | |
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| Partner organisation: | UoS MAPP Hub, Rolls Royce, Tinsley Bridge LTD |
| Project name: | Business case for IoT instrumentation of existing machines: A Laser Based Additive Manufacturing (LBAM) use case |
| Project type: | Research |
| Funder: | Pitch-In UKRI |
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| **1. Project activity** | |
| What did you do? Please provide a short overview of the project activities, indicating how these compare to the planned deliverables. Please indicate the reasons for delivering more or less than originally planned. | |
| This section both highlights and provides the technical detail of research and outcomes occurred over the duration of this project. It is structured as such that the key highlights, deliverables and any mitigation strategies employed are shown in the beginning, before delving into the events and work undertaken. This section covers the majority of work surrounding the initial goal of this research, the need to move towards a real-time data processing framework that will use machine vision and machine learning to build automated detection of process characteristics linked to defect generation in LBAM, and look to address the key barrier of business case development in the implementation of IoT; this is demonstrated by the exploitation of IoT for in situ sensing of parameters for LBAM process.  The proposed use case focuses on exploiting IoT for monitoring and control of two key LBAM parameters: Monitoring powder flow rate: Variations in powder ﬂow resulting from disturbance in chamber backpressure, powder clogs or other instabilities affect the laser beam interactions with the feedstock and can lead to process instability. Monitoring the thermal history of full part and not just the melt: In the absence of any mechanical processing, the microstructural evolution of the part is determined solely by the thermal history during the process.  This was set about through the following aims and objectives:  **Aim:** The aim is to develop and document a business case and a supporting demonstrator for an IoT solution on an existing manufacturing process using LBAM as a use case.  **Objectives:** The aim will be achieved through the following objectives:  1. Develop a monitoring system for powder flow rate using available loss-in-weight feeders and multi-modal sensors.  2. Develop imaging setup using infra-red and temperature sensors for historical capture of thermal history beyond just the melt pool.  3. Develop a business case template that could be used for implementation of IoT on existing industrial processes.  4. Develop a working demonstrator and supporting educational material to inform businesses on the costs, benefits and return on investments of IoT implementation.  In addition to this research a number of additional outcomes have been achieved, including the Github repository, and a number of tools made available freely for users of the machine and a technical report outlining our work, technology identification and integration into the LBAM machine for future use.  The remainder of this section is broken down into the following, firstly section 1 covers key highlights, deliverables and mitigation strategies, section 2 discusses the LBAM work environment and the challenges associated with integrating technology and gathering real-time process data. Next in section 3 we discuss the development of all hardware platforms, and their integration into the work environment and initial data processing that occurs on these platforms. Finally section 4 outlines the research into the LBAM process characterisation developed throughout this project, before section 5 offers conclusions and future considerations.   * **Key highlights, deliverables and mitigation**  |  |  |  | | --- | --- | --- | | **Work Packages** | **Deliverables** | **Status** | | WP1: Monitoring mass flow rate  WP2: Thermal characterisation of melt pool and material structure | Real-time data pipeline for thermal imaging of LBAM process.   * Thermal camera platform * Hall sensor platform * Weight sensor platform * Scraper RPM platform * HDF5 data pipeline | The backbone of this project is complete, with the development of four hardware platforms for process monitoring, we initially started with just the thermal camera setup before expanding in scope to other sensing modalities. For each hardware platform there exists plans on integration into LBAM machines, our data pipeline for capturing and storing of data along with initial pre-processing. | | WP1: Monitoring mass flow rate  WP2: Thermal characterisation of melt pool and material structure | Online thermal characterisation   * Original BEAM thermal camera laser radius estimation * Original BEAM thermal camera laser power estimation * Hatch spacing characterisation * Thermal image upscaling through CNN methods * Unsupervised thermal imaging melt pool segmentation * Hall sensor characterisation of melt pool magnetics * Powder flow process monitoring * Magnetic Impedance Tomography | Complete, but with a reduced scope. The initial work package and deliverable that centred on the need to characterise the thermal data generated from the melt pool was completed, using a number of methods (laser radius, power, melt pool size). However, the transition to a more real-time platform beyond just data gathering, but including online modelling and analysis proved difficult given the nature of image processing and low scale CPU power of IoT solutions. This was mitigated through the exploration of alternative sensing modalities (hall sensor, powder flow rate monitoring, MIT) to gather further data for characterisation but in more real-time. We have also looked towards the future with a EPSRC proposal around the use of edge computing and light-weighting of machine learning models for AM. Additionally we would have liked to have gained some material defect data of the build, through SEM inspection but this was put on hold until after lockdown. However plans are in place to begin this experimentation when access allows. | | WP2: Thermal characterisation of melt pool and material structure | Historical digital twin   * Process parameter mapping of laser head and powder flow rate * Melt pool size and 3D surface reconstruction * Melt pool size spatio-temporal modelling through flying edge | The development of a methodology and software framework for the offline modelling and analysis of the melt pool (aka a historical digital twin) has been completed and tested. Two main approaches were developed, the first a 3D reconstruction approach using the captured thermal imaging data. Secondly, a 2D frame by frame slicing approach for estimating the thermal surface area of the melt pool. Both methods retain the dynamics of the build, similar to that of the original BEAM camera. |   The remaining sections discuss activities undertaken and their relation to the underlying work packages (WP) and deliverables. They also include our experience and thoughts on the challenges and benefits of IoT sensor integration and the development and use of machine learning. The table of contents provides reference to each section below:  **Table of Contents:**   1. Work Environment and Challenges - pg 4 2. Hardware Development, Integration and Data Processing - pg 5    1. Thermal Imaging Platform - pg 5    2. Hall Sensor Array Platform - pg 8    3. Powder Flow Weight Sensor Platform - pg 11    4. Powder Flow Image Sensing Platform - pg 15 3. LBAM Process Characterisation - pg 23    1. Wavelet Characterisation - pg 24    2. Process Parameter Characterisation - pg 24    3. Estimating Melt Pool Size - pg 31    4. Thermal Image Upscaling - pg 38    5. Unsupervised Thermal Imaging Segmentation - pg 39    6. Magnetic Impedance Tomography - pg 44 4. Conclusions and Future Considerations - pg 45 5. **Work Environment and Challenges**   The goal of the platforms as per WP1 and WP2 was to create a real time data pipeline for collecting information about the build site through the integration of a number of IoT based sensors, particularly for thermal imaging but also beyond this into other areas of interest. This can be broken down into two main tasks, the first being the identification of suitable hardware and its integration into the LBAM environment. Secondly the development of a suitable data pipeline to capture, pre-process and store everything of value produced from these sensors during and after the build. This report will not go into a lengthy discussion on how the sensors were chosen, but they fall on the need to capture thermal data, hence the choice of a cheap thermal camera, and finally to explore alternative sources of process variation form available IoT tools, in this case the use of ‘Hall sensors’, IoT grade weight sensors and a cheap RGB camera. The final two sensors were an addition to this project to explore variation from the powder flow processes that feed the material during the build, something discovered during early discussions with technicians of the BEAM machine.  As a result, four hardware platforms were developed to collect real time in-process data about the BEAM machine. Each platform collects a different type of data about the machine and the build site storing it locally. All platforms were developed using IoT (Internet of Things) hardware and act independently of each other storing the logged information locally. Each platform uses a different sensor and measures a different type of information.  One of the particular features of interest was the melt pool where the metal powder is melted by the laser to form the structure of the material. This isn’t often recorded or inspected during the build process as it’s often difficult to fit sensors that can see it. As the features of the melt pool are related to those of the build structure and by extension quality, monitoring it through different sensors and characterising it are of great interest.  The biggest obstacle with developing the platforms was the environment. Once a build has started, the build space is sealed to prevent metal powder from entering the air and becoming a wider health hazard. The build process and any hardware inside can be monitored through several port holes, but if something goes wrong they cannot be accessed until the appropriate procedures are followed rendering the environment safe. For some materials, additional PPE is required to even enter the environment and open the door. Additionally, the metal exterior of the BEAM machine prevents remote access from an outside source. Furthermore, the existing wiring prevents any platforms from being connected to an outside power supply meaning they have to be independently powered through a battery system. All the platforms developed during this project were powered using a rechargeable battery.  It has been confirmed by the BEAM technicians through experiments that the BEAM machine does not fully utilize the powder that is fed into it and a significant portion of the powder is distributed across the surrounding area. Therefore, any platforms need to be protected in some fashion to stop any metal powder from damaging components or causing a short circuit. This can be as simple as a plastic box or something more elaborate depending on the gaps needed for components.  The next problem is temperature. The BEAM machine’s laser can emit a maximum of 2 Kilowatts (kW) but is typically used under 1 kW. The energy is concentrated into a small area and is designed to melt metal so there was some concern about the temperature at the edges of this area impacting or damaging components. At minimum, this can be mitigated through the casing needed to protect it from stray powder and at most would require some sort of cooling system such as a fan.  These are just some of the challenges faced when looking to integrate IoT sensors within the working environment of this particular LBAM machine.   1. **Hardware Development, Integration and Data Processing**   Described in this section are the four main hardware platforms developed and test throughout the project along with initial data analysis of the AM process data generated and captured by these platforms.   * 1. **Thermal Imaging Platform**   The first platform is a low resolution thermal camera connected to a Raspberry Pi that reacts to the subsurface radiative heat of the build site. As the camera cannot provide a direct measurement of the temperature inside the build site, it is instead used to monitor how the heat is distributed through the melt pool. Abnormalities in the distribution could be an indicator of a defect. It is also a rare opportunity to monitor subsurface power distributions that is often difficult to monitor. The information is stored in a compressed HDF5 file locally on the Pi. This file format was chosen for its ability to store multidimensional datasets and compress them. This ability to compress will save a lot of space especially for long builds. The main downside with the format is it has to be explicitly opened and closed so if a power failure occurs the file becomes inaccessible. The recording program is designed to operate for a fixed period of time to ensure that the file is safely and correctly managed. The data can be partially recovered if needs be by reading in the file as a large vector of raw bytes, reshaping it into the known shape of the data and converting to the appropriate data type. Some data is corrupted due to the metadata being blended with the collected data. Better tools would need to be developed for a complete recovery.  As the interior of the build machine does not have any fixtures or mounting points for sensor platforms, a custom mounting beam was designed and 3D printed. The build plates are attached to a circular platform in the approximate centre of the room. This platform has a number of troughs cut into it going from the outer circumference towards the centre. This printed beam is designed to fit into one of these troughs and keeps the camera at a fixed angle relative to the build plate. As can be seen in the images below, the platform was housed in a plastic case to protect it from the powder and heat. The case is mounted to the beam by a central screw and can be attached at one of several points along its length.    *Figure 1: Thermal camera platform prototype. Left image is the platform as used in lab testing. Right image is the finished platform with a case and printed mounting beam.*  The platform has been used to record two builds; a complex arrow shape and three parallel lines. The arrow shape was composed of a main triangular arrow head and three rectangular tails components. The image below in figure 2 shows the platform in use during the arrow shape build. Ideally the camera would be positioned parallel to the long build edge to ensure information is perceived uniformly across the camera. As this was the first practical test with the platform, the main concern was with the robustness of the system and the core functions of the recording program.    *Figure 2: Thermal camera platform in during the arrow shape build.*  The second image below in figure 3 shows an example of the data collected by the camera converted to grayscale. The camera captures at a resolution of 24 by 32 pixels and perceives 1 ℃ changes in the radiative heat. A total of 332,583 frames of information were captured with the build composing 58,602 frames. This ensures that the entire cooling period is captured along with information about the nominal background temperature. The thermal activity generated by the laser was perceived in the middle third of the image. The white blob seen is the point of contact between the laser and the build plate and contains the sub-surface power density of interest. The line bisecting it is believed to be the laser path. The information collected has clear distinct data artifacts with a definitive shape that can be processed further. The main limiting factor found with using a camera perceiving radiative heat is the effective sensing distance is a lot shorter than originally estimated. Despite the temperature travelling through a thermal conductive material such as metal, the temperature drops off sharply with the perceived boundaries of the heating area rapidly losing definition as the laser head moves away. A more expensive infra-red camera may be able to overcome this obstacle as it calculates temperature from the emitted light, but there is no known infra-red camera that is within the IoT price range due to the expensive optics required and inherent manufacturing costs.    *Figure 3: Example of the footage captured by the thermal camera.*  When the maximum temperature of each frame is plotted we can see each portion of the arrow shape and its distinct dynamics. The highlighted portion of the plot shows what is the dynamics of two of the rectangular tail portions and the main triangular head.    *Figure 4: Maximum temperature recorded during arrow shape build. The highlighted region is believed to be the*  Unfortunately, the battery died during the three lines run causing the file to be improperly closed meaning the data is lost. Attempted recovery of the data showed that very little data was actually recorded and the data didn’t appear to have any significant artifacts and so was most likely recording during the time allocated before and after the build started. This period to capture the state of the material before any heating and the cooling that occurs afterwards. A learning experience, which we took forward by altering the software to allow for periodic saving of data and the addition of LED lights to indicate the current running state of the platform when it is isolated within the LBAM environment.   * 1. **Hall Sensor Array Platform**   The second platform is an array of Hall sensors that passively monitors the magnetic response from the build site and an additional Hall sensor to act as a reference signal for the magnetic baseline of the environment. The array is arranged horizontally to record the response across the length of one side of the build plate. They are recorded using an Arduino Uno and are logged to a CSV (Comma Separated Values) file stored on an SD card. The image below on the left shows the hardware from a side view. The orange platform at the top is a Tinkerkit sensor board designed to make it easier to connect and disconnect the sensors. The dark blue platform in the middle is a Wifi board that manages the connection to the SD card and the light blue one is the Arduino Uno.  This sensor was chosen as electromagnetism has been proven to be a non-invasive way of inspecting the interior of a range of material both biological and metallic. The idea was the magnetic response, if any, would be an indirect way of measuring some aspect of the melt pool as it is known that the movement of molten metal can generate a magnetic field.  *Figure 5: Hardware of the Hall sensor platform. Arduino Uno (bottom), Wifi Board (middle) and Tinkerkit Sensor Board (top). Bank of 5 hall sensors (right)*  The platform was used to record a build composed of three lines parallel to the monitored edge of the build plate. The lines were spaced equally from each other and at an increasing distance from the plate edge. Surprisingly, the recorded data had distinct artifacts and dynamics and wasn’t too noisy despite the cheap sensors. As it’s highly uncommon to use electromagnetism for in-process monitoring, more data is required to better determine the nominal features and best form of analysis. The main issue that was found with this platform is the sensitivity of the sensors. It was discovered that the blue box with the screw, which can be seen in the right hand figure above, changes the sensitivity and is likely the cause of the offset between the different channels seen in the plot below in figure 6. While it’s useful to adjust the behaviour of the sensors, the sensitivity, and by extension the measured strength of the magnetic field, can only be estimated using the sensitivity range from the datasheet and the angle of the screw.    *Figure 6: Data recorded using the Hall sensor platform with each line representing a different sensor. The highlighted region is the first track recorded in the three track build.*  The figure 6 above shows the signals recorded by the array of Hall sensors with each line representing a different sensor or channel. Each group of dynamics in the data corresponds to a different track that was printed. The smallest group with the sharp spike in the beginning corresponds to a track that was stopped early by the operator as the laser power was set incorrectly. The highlighted region is the first completed track and was closest to the sensors.  Analysing this data is a bit difficult as the dynamics of each track is different and inspecting it shows that the minimum value of each signal rises over time. This means using windowed Fourier analysis on each track is unlikely to work due to spectral leakage caused by the changing global dynamic. A better tool is Wavelet analysis which is used to identify time varying dynamics in a signal. A chosen signal called a mother wavelet is convolved with the data and the response indicates the presence of dynamics with a certain period. The introduction of a distinctive dynamic could indicate a defect or alternatively the wider introduction of dynamics outside of the defined norm could be an indicator. The plot below is a scaleogram of the data recorded by the first channel during the first track. This type of plot is used to show the results of the wavelet analysis. A high value on the plot indicates the presence of a dynamic with the corresponding period at the corresponding time. As can be seen in both the scaleogram and the line plot, the main dynamics present throughout the track have a period between 8200 and 8800 milliseconds. The scaleogram also has approximately 25 areas of activity. The operator informed us that each track involved 25 laser pulses and it is estimated to have a period of 8500 milliseconds between pulses. This suggests, as suspected, that the thermal behaviour generated by the laser is causing the magnetic behaviour.  It was noted by the operator during the build that the surfaces of the tracks were not smooth and would likely have bumps across them. This has not been confirmed through visual inspection afterwards and or scanning with a SEM (Scanning Electron Microscope). It is theorised that the variations in the peaks of the response correlate with the changes in the build surface but this will also be influenced by the laser being physically away from the sensor.    *Figure 7: Scaleogram of the first channel (blue line in the previous figure) showing the different dynamics identified through wavelet analysis.*   * 1. **Powder Flow Weight Sensor Platform**   The third platform is a weight sensor platform designed to measure the weight of the powder hopper supplying material to the BEAM machine.    *Figure 8: The hoppers used to hold and feed metal power for the additive manufacturing process.*  The mass flow rate has a direct impact on build quality as not enough material to certain sections will greatly impact the build quality, structural stability and performance of the work piece.    *Figure 9: The illustration of powder feeding during printing processing.*    *Figure 10: The stability problem for the flowrate during the printing process.*  Currently there is short of the measurement methods to monitor the flow rate in the real time during the printing process. At present, the mass flow rate is estimated before builds to test the health of the hopper and there is no continuous measurement system in place. The hopper is disconnected from the machine and powder is fed through it into a container at the end placed on a set of digital scales. The scale is measured at regular intervals and the mass flow rate is estimated from this.  An offline calibration is carried out before the actual printing process. A weight scale is used to measure the fed powder in a time window, under an empty load printing operation, which the laser is not activated. The flow rate is calculated as the total weight collected divided by the length of time window. This calibration method is complex to conduct due to the safety issue from the metal power, that it has to separate and seal the printing cabinet within the printing machine with outside space, to avoid the metal power getting into the human body. The measurement operator also needs to wear appropriate PPE equipment to carry out this kind of calibration. So that it is necessary to develop a method to measure the flow rate in real time and can send the measurement data remotely.    *Figure 11: The weight scale used to calibrate the powder feeding flow rate (inside of the BEAM machine).*  The platform consists of a Raspberry Pi and a 2 kilogram load cell connected via an analogue to digital converter. The measurements are recorded and logged to a database running on a Raspberry Pi.    *Figure 12: Developed IoT weighting solution which can measure the flow rate remotely in real-time*    *Figure 13: Developed IoT weighting solution use wireless communication to send the data remotely*    *Figure 14: Diagram showing the flow of information in the weight sensor platform and how flow rate is calculated.*  The above figure shows how the information is processed and stored on the database. The measurements are averaged before being sent for processing to minimize the impact of noise. The mass flow rate is calculated as the difference between two averaged measurements divided the time between those measurements. The time of measurement for the flow rate is set as the time the information is written to the database.  Chart  *Figure 15: Experiment results of using IoT weight sensor to measure flow rate*  This project has accomplished one experiment run before the lock down. Additional experiment and validation may continue after the release of lock down.  To validate the performance of the developed IoT weighting solution, following a high precision weight scale and professional weight sensor would be used for comparison. It is expected that the IoT weighting solution may have lower accuracy compared to the expensive industrial sensor. However, it is worth coinciding the trade off between the cost of IoT solution (totally with £50) and industrial solution (only the weight scare worth £400, the industry flow sensor would cost more than £1000), and the convenience which IoT solutions provide, such as wireless communication, real-time data logging and display functions.   * 1. **Powder Flow Image Sensing Platform**   A fourth platform was also planned to monitor a component inside the powder hopper known as the scraper. Powder is fed from a container into an area where a spinning plastic scraper collects it and combines it with a carrier gas that brings it inside the BEAM machine. The powder mix is then ejected into the path of the laser where it is melted to form the build structure. Through the investigation into the mass flow rate, BEAM technicians found that there was a correlation between the target scraper speed and the standard deviation of the flow rate. It was found that a specific region of speeds causes the flow rate to become highly unstable.    *Figure 16: BEAM hopper showing internal turntable scraper (middle white)*    *Figure 17: Plot of the mean mass flow rate for Stainless Steel 316 plotted against target scraper speed. The bars are the standard deviation on this flow rate.*  The above plot shows the results of these trials. Different percentages of 10 RPM (rotations per minute) were trialled and the mass flow rate was measured. The standard deviation was monitored as a measure of stability. As can be seen above, the standard deviation increases drastically between 5 and 15 percent of 10 RPM. It is believed that this increase is caused by a resonance with the sensor as the measurement system used operated on a tuning fork principle.  Analysing the raw data for each plot point reveals some interesting dynamics. When the popular Fourier analysis is applied, a definitive change is observed in the problematic range of speeds, but unfortunately doesn’t reveal many specifics. This implies irregular dynamics that are not consistent across the datasets.    *Figure 18: Spectral power plots of the Fourier analysis results for each target turntable speed.*  A tool that proved to be more insightful is Wavelet analysis which is designed to reveal the periods of time varying dynamics. The plot below shows the results of the wavelet analysis of the 4 percent speed data. The spikes seen below are brief occurrences of dynamics in the data. The width is the time period they occur in and the height is the estimated range the period of the dynamics occurs in. There is clearly no consistent dynamic indicative of a resonance, but each of the spikes do fall within the same general range of between 0.1 and 0.7 minutes.    *Figure 19: Scaleogram of the mass flow rate data for a target scraper speed of 4% of 10 RPM.*  When Wavelet analysis is applied to the data with a larger standard deviation the plot below is generated. The consistent activity across the entire plot reveals a consistent dynamic occurring throughout the dataset. This is in line with the theory about a resonance occurring at certain speeds. The observed dynamic has a period somewhere between 0.02 and 0.05 minutes.    *Figure 20: Scaleogram of the mass flow rate data for a target scraper speed of 10% of 10 RPM.*  At present there is no continuous measurement of the scraper speed. The speed is set at the start of a build but it is not actively monitored or recorded. The scraper’s motor is not easily accessible due to the construction of the hopper and the requirements about handling powdered metal do not permit cutting holes in the exterior. The only option is to estimate the speed from the outside.  The designed platform uses a camera to track the scraper and estimate its speed. A coloured marker would be added to make the scraper easier to track as the container, whilst transparent, is highly reflective. The hardware chosen for this platform is the Raspberry Pi 4 and the Raspberry Pi Camera Module v2. The Raspberry Pi 4 was chosen over version 3 as it has more memory and will process the received images faster. The camera was chosen due to its native compatibility with the Raspberry Pi, high resolution and ease to configure the balance between resolution and frame rate. A higher resolution means a better quality image but would take longer to process and an overall lower frame rate.    *Figure 21: Picture of the hardware for estimating the speed of the scraper inside the powder hopper. The Camera Module v2 is highlighted in red and the Raspberry Pi 4 platform is highlighted in blue.*  As extended access to the machine was limited due to project circumstances and the Coronavirus lockdown, as a mitigation, possible techniques were evaluated using a rotating dot animation designed to emulate the coloured marker placed on the plastic scraper and development of the first version of the platform took place in a non-work environment. As object tracking is a well-researched area, having synthetic data to evaluate performance helps speed up development and allows development to continue in lock-down. Development was further sped up by only looking at already implemented tracking methods. Support for four different types of trackers was developed each tracking movement in different ways.   1. The first tracker tracks the dot by first masking the image to just colors within a target range. The target range is in the HSV (Hue-Saturation-Value) color space as neighbouring numerical values Edges that enclose a shape known as contours are then found and filtered for the largest one. This assumes that the largest contour surrounds the dot and the others are noise or light artifacts. The moment of this contour is then found and is taken as the centre of the rotating dot. The difference in position when compared to the last measurement divided by the time between measurements gives the estimated velocity. This is the simplest tracker and the most stable as it doesn’t rely on complex analytics or deeper levels of processing. However, it is influenced by lighting artifacts that destroy parts of the image or impacts the contours causing false objects to be detected or the contours of smaller objects to merge giving the impression of a large object that is easily confused as the target. Also, a static target color range can mean the dot may be lost with changes in lighting conditions. Practical testing will likely reveal that denoising or sharpening filters will be required to improve efficacy.     *Figure 22: Example of the output of the ball tracker with the different stages of processing shown. The trail in the results is the history of the tracked centroid’s position and the yellow circle is the detected boundaries of the dot.*   1. The second tracker is called Lucas-Kanade (LK) and falls under a class of techniques known as optical flow which attempts to look at the movement of colors between images and estimate their velocity. It can be thought of as estimating the velocity of an object from its motion blur. This method assumes that a given target pixel of a certain intensity and its nine surrounding neighbours have very similar, if not the same, motion. This allows us to form a set of equations describing the change in the pixel’s intensities between frames as a function of time. The solution of this is called the optical flow vectors denoting the estimated movement in the respective directions. Tracking every single pixel is clearly inefficient as not every pixel is of interest. Instead, practical applications of this algorithm find the points to track in the first frame using an algorithm such as Shi-Tomasi which finds the corner points of a shape. This project used the version implemented in the OpenCV image processing library whose examples use the Shi-Tomasi algorithm. As the tracked points can be easily lost or have their defining features lost with changes in lighting or environment, this project’s application renews the points to after a fixed interval of frames. The velocity of the dot, like with the first tracker, is estimated by finding the moment of the tracked points and dividing the change in position by the time between frames. This act of renewing the features in theory could make the process more robust to changes in the environment, but this robustness is dependent on the choice of feature detector. In testing, different feature detectors will likely have to be trialled in order to find the most suitable.     *Figure 23: Example of the output of the Lucas-Kanade tracker. The coloured dots are the different points being tracked.*   1. The third tracker is called Gunnar-Farneback and is referred to as a dense optic flow algorithm as rather than tracking a representative, sparse number of points, it tracks all points in the frame looking at the changes between two frames. The algorithm returns the optical flow vectors for every pixel as a two channel array. The results are converted into magnitude and direction matrices and then converted to a HSV image where the magnitude is Hue and the direction is Value. The coloured magnitude matrix is then masked and processed for the more sizable artifacts in the same way as the first tracker. The colouring provides a visual way of displaying and recording results that is easier to inspect afterwards. In addition, it is faster to write to a media file such as an MP4 file rather than a numerical data format like the HDF5 file used with the thermal camera platform. This tracker clearly operates slower than the previous tracker due to the increased amount of information required. This can be minimized through downsizing the image or similar augmentations and adjusting the algorithm’s parameters. Like with the first one, this tracker can be easily influenced by lighting conditions which may be detected as the very fast movement of pixels resulting in anomalous artifacts or high intensity noise in the results. Filtering of velocities outside the known limits of the scraper may help reduce noise and remove artifacts.     *Figure 24: Example of the output from Gunnar-Farneback tracker. The blue diamond is the estimated centroid.*   1. The final tracker is based on a popular indirect measurement technique called a Kalman Filter. The goal of indirect measurement is to estimate a parameter that cannot be measured directly due to restrictions in the environment or available sensing technology through the measurement of related parameters. A Kalman Filter is based around a model which describes how the measurements and target are updated between measurements. Each variable is described as a combination of the previous value, the impact of several of its derivatives over the time between measurements and some estimate of the system noise. The weights associated with each variable are updated through measurements supplied by the user. The filter looks at the difference between its own estimate of the measured values and the given measurements and makes adjustments based on the difference. As the user supplies more measurements, the difference between the filter’s estimate and the measurement becomes smaller to the point where the user can rely on the filter’s estimates. This technique has proved to be effective in a variety of situations including tracking. The main disadvantage is the obvious requirement for data in order to train the model and evaluate it. Additionally, the noise model parameters can be difficult to estimate and have a considerable impact on performance.     *Figure 25: Example output of the Kalman tracker. The green circle is the estimated centroid position. The red trail is the history of the actual centroid position estimated using the first tracker.*   1. **LBAM Process Characterisation**   The previous section outlined the main hardware platforms that were developed during this project, there integration and some early pre-processing and data analysis collected during a number of build runs of the LBAM machine. This section continues with further analysis and algorithm / tool development of the data collected to better improve the characterisation of the LBAM processes, in particular that obtained from the thermal imaging sensor. This includes research on online thermal characterisation of the melt pool and development of a thermal fingerprint framework for capturing and modelling the historical 3D melt pool characteristics during a build.  After completion of WP1 and the hardware and data pipelines, this project moved on to methods for further characterisation of the thermal imaging data in both online (real-time) and offline modes. Below are a number of algorithms and software tools developed during this project to achieve these aims and the associated deliverables for WPs 1 and 2. Though these were successfully completed, the recent events of the lockdown have reduced the scope and ambition a little as a result. The biggest change is the delay in obtaining SEM and material inspection data on the builds to better assess any failures, and quality reduction that occurred during the build and more rigorously linking this to the run data and characterisation analysis. As a mitigation we have sought to resume experimental runs and capture this data when lockdown is lifted and access to the BEAM machine becomes available.   * 1. **Wavelet Characterisation**   Applying wavelet analysis to the maximum temperature found in each thermal image from the arrow shape revealed a main dynamic with the same period as when the laser was pulsed. Dynamics outside of this are the likely combination of sensor noise and unique material dynamics.    *Figure 26: Scaleogram of the Max Temperature*  Like the popular Fourier transform, the Wavelet transform can be extended to multiple dimensions. When applied to two dimensional data like thermal images, the data is decomposed into sets of coefficients each representing the different ways the dynamics are combined over the axes, X and Y in this case. Like with the one dimensional case, the presence of known abnormal dynamics could be an indicator of a defect. However, due to the low resolution of the camera and the amount of space each pixel represents, some interpolation algorithm may be required to get any meaningful spatial dynamics.   * 1. **Process Parameter Characterisation**   Another form of characterisation possible is the estimation and monitoring of process parameters and comparing them against the target. Certain process parameters have a substantial impact on the build quality and are only set at the beginning. In addition the BEAM machine had already incorporated a more expensive thermal imaging camera set down the laser path directly over the build site. Later another set of cameras (thermal / UV) were instrumented separately by the technicians to gather more data during the build. This data was passed on to us for further analysis.   1. Hatch spacing is the distance between the lines used to form the layers of the build. This impacts the porosity of the product and its build quality. It can be estimated by inspecting the history of the laser head position recorded by the BEAM machine. This information is logged by the laser head’s motor controller and is not easily accessible to allow real time monitoring. The history includes the head’s position in the different axes, the velocities and current supplied to the motor. The motor’s controller logging this information is an independent system from the other control systems inside the BEAM machine. Below is a plot of the laser head position history for the arrow shape build.     *Figure 27: Laser head position history for the arrow shape build.*  The hatch spacing can be estimated by looking at the difference in the Y-position of the laser head for each layer. The plot below shows this for one of the rectangular objects. The hatch spacing is estimated as the average of these differences and is represented as the dotted line in the plot below. The average can be safely taken as the variance in the differences is very small.    *Figure 28: Region of the difference in laser head’s Y-position. The green line is the average difference for this region.*   1. The laser radius can be estimated using the thermal camera installed in the BEAM machine. Two cameras were used in the course of the project, both connected to the laser head. The first camera was connected parallel with the laser head and monitored the surface radiative heat of the build site. This provided information about how the laser power was distributed. The radiative heat values are recorded to a H264 video file in a proprietary way and there was no documentation on how to extract the information. Researchers and BEAM technicians worked with the BEAM machine’s manufacturer to reverse engineer the format and extract the values. An example of the information recorded converted to a grayscale color scheme is shown below.     *Figure 29: Example of footage captured with the first thermal camera.*  The second camera was fitted in line with the laser head and inspected power distribution by siphoning off a portion of the laser. No useful data was recorded using this camera due to technical issues with calibrating it.    *Figure 30: Example of the data that was collected by the second thermal camera plotted using the HSV colormap.*  Using image processing techniques and footage from the first camera, the laser radius can be estimated. A consistent laser radius means the laser power is distributed uniformly meaning the heat is distributed smoothly across the build. If the metal powder does not receive enough heat, pockets of un-melted powder are left in the structure affecting build quality and adhesion between layers.  In order to estimate the radius, the laser power density had to be estimated from the radiative heat data. A model has been developed using data points about material parameters, such as material conductivity, collected from datasheets. As the material parameters are for irregularly spaced temperature ranges and datasheets don’t contain many points, the model is heavily approximated. Splines are fitted to the data points to permit prediction between the data points.  Once converted, the e-2 method is applied to estimate the radius. This is a developed method that is agreed upon by multiple institutions as being one of the certified methods for calculating it. It involves finding all the power density values that are above e-2 times the peak value, estimating the physical area these values occupy and calculating the radius. This assumes that the area is circular and by extensions the formula for the area of a circle can be applied. The figure below is the results from applying this method to the footage recorded during the arrow shape.    *Figure 31: Estimated laser radius using the e-2 method.*  The estimated value is erratic bouncing between 0 and 0.0004 metres. The gaps between are when the laser is turned off. To find an acceptable averaged value a number of filters are applied. First all the peaks in the data are found and then filtered for those that are greater than 5% of the maximum. This removes the values for when the laser is turned off. The set tolerance is arbitrary but seems to be effective. Next the data is filtered for those within three standard deviations of the mean. This is a common practice for removing values that are outside the majority of the behaviour such as the peak at the beginning, known to be caused by a defective frame captured by the thermal camera. The new average of these filtered values is then calculated and taken as the estimation of the laser radius. The plot below shows the results at the different stages of these filters ending with the green line representing the final estimation. For reference the target laser radius is 0.35 millimetres.    *Figure 32: Plot showing the different stages of filtering applied to the estimated laser radius.*  The thermal camera cannot be accessed in real time at present due to how it’s wired into the machine and the fact the information is logged to a video file meaning multiple processes can’t access it.   1. The laser power can be estimated by converting the footage to laser power density, identifying the heating boundary and integrating the values within. The physical size of the identified area is calculable as the camera doesn’t have an angular field of view meaning each pixel lines up with a rectangular area. Luckily the datasheet contained the conversion value known as pixel pitch for converting the area from pixels squared to metres squared. Several techniques were trialled to find the closest power estimate using the arrow shape footage where it is known the laser power was set to 500 Watts. The method that yielded the closest estimate was the Hough Circle transform which attempts to find and estimate the radius and centre of circles in the image. Each circle is weighted as an indicator of whether the circle exists in the image. Below is a power estimate plot using the Hough Circle implementation in the SciKit Image processing library (SKimage).     *Figure 33: Estimate of the laser power using the highest scoring circles found using the Hough Circle function.*  Each frame is normalized by its local limits and rescaled to an 8-bit image. A limitation of a lot of image processing algorithm implementations is the requirement for it to be either a 8-bit or 16-bit unsigned integer matrix. The Skimage library has some support for floating point images but not in this algorithm. The Hough Circle algorithm is then applied to build a list of detected circles. The list is then filtered to remove circles that go out of bounds of the image. Visual inspection of the collected information shows that the heating area always remains within the bounds of the image. The circle with the highest score given the algorithm is then used to calculate the laser power.  Skimage’s implementation of the Hough Circle algorithm was used as it is a more direct application without any pre-processing that impacts the results. The alternative implementation in the popular OpenCV library uses a Canny thresholding algorithm to pre-process the image and try to filter out noise. Whilst Canny has proved to be effective in a wide range of circumstances, it doesn’t appear to be effective with the locally normalized images. The main downside with Skimage’s implementation is it is very slow as the library is implemented purely in Python compared to OpenCV whose backend is written in C++ which is faster. If this was going to be used in a real-time pipeline, the direct implementation would have to be re-written in C++ or similarly fast language.  The laser power approximation is an underestimate, compared to the target 500 Watts, as the thermal camera only records the surface and not the subsurface. It should be noted that the BEAM machine does record the laser power in an internal log file along with several other parameters, but it is sampled at a very low rate compared to the other sensors making any comparison pointless.   * 1. **Estimating Melt Pool Size**   Estimating the subsurface laser power to calculate the remaining power is a difficult task. First, the thermal camera used in the developed platform has an angular field of view of 55 degrees meaning the perceived area doesn’t linearly scale with the distance from the sensor to the melt pool. Secondly, the thermal camera reacts to radiative heat which in this case is travelling through the build plate and a forming melting structure that is constantly changing. The build plates are always Titanium whilst the metal powder can be one of any number including copper blends which are notoriously difficult to control. This makes accounting for the material and distance very difficult, likely requiring a complex model.  A slightly more unusual form of characterisation is the estimation of the melt pool volume and surface area of the heat distribution. The developed thermal camera platform described in section 3.1 observes how the heat supplied by the laser is distributed and heats up an area that includes the important melt pool. As mentioned, interruptions in the heat distribution could indicate a defect in the structure. This could have an impact on the estimated surface area and the volume of the heating area. Normally the area and shape of the melt pool is only inspected after the build using a scanning electron microscope.  The surface area is estimated using the footage from the Raspberry Pi thermal camera platform and a number of edge detection algorithms.   1. The first method is based around the Sobel edge detection algorithm which calculates the derivative of the image using a custom operator that is convolved with the image. This derivative is directional and can be calculated for both the X and Y axis. The developed algorithm calculates the derivatives in both directions, normalizes them and combines them together like finding the magnitude of a vector. The high values in the resulting matrix provide a good indication of where an edge is. This matrix is then thresholded using the popular Otsu algorithm, which calculates the threshold value for you, to separate the useful values from background noise. Contours are then found and the area of the largest one is then calculated. This is taken as the size of the heating area. The plot below is the estimated surface area using this method.     *Figure 34: Estimated surface area using the Sobel-based algorithm*  The most interesting feature of the above plot is the artifact that occurs approximately between frames 90,000 and 150,000. It closely resembles the maximum temperature behaviour believed to be associated with the triangular shape of the arrow build. The fact that it shares features suggests that this period of estimation may be accurate. Given that the input images tend to be very noisy, it’s not too surprising that area estimates are also noisy as the background noise messes with the heating boundary.  Compared to a black box function, this method offers more configurability but requires more tuning to find the correct threshold that separates the background and noise from the thermal activity.   1. GrabCut is a more recently developed algorithm attempting to solve the difficult problem of separating a foreground object from the background. In this case the foreground is the thermal behaviour generated by the laser. Unlike other solutions to this problem, this algorithm requires little prior information about what separates the two. In this context, the prior information is the area the thermal activity occurs in as it mostly moves horizontally in the middle third of the image. From this initial labelling, GrabCut estimates the Gaussian Mixture Model (GMM) for the background and foreground. This model describes the distribution of pixel values that compose the foreground and background as a combination of several gaussian distributions.   A graph is then built from this distribution with each node being a pixel from the image.  The foreground and background have an assigned source and sink node, respectively, within the graph that every node is connected to. The edges connected to these nodes have a weight based on the probability of the pixel belonging to the foreground or background. The weights for the edges connecting pixel nodes to each other are based on the similarity between the pixels. A large difference between two pixels will receive a low weight.  The nodes in the graph are then separated into two groups, the foreground and background, using a cost function based on the sum of the weights. This cost function is the energy required to separate the pixels into the two groups and the algorithm repeats this process until the cost is minimized. This act of optimization is what helps the algorithm produce high quality results. The generated mask is then searched for contours and the largest one is used to calculate the area.  However, like with all optimization processes the process can fall into a false minimum causing incorrect results. This means that the masked results need to be inspected, especially with this noisy thermal data, to check for poor results or cases where the point of emittance so if the laser is too far away from the thermal camera. In this case, the boundary of the heating area is easily lost due to the temperature dropping off sharply.    *Figure 35: Estimated surface area estimated using the GrabCut algorithm*  The plot above shows the estimated surface area using this method. Like with the first algorithm, a distinct change of behaviour is observed in the approximate 90,000 to 150,000 region. Unfortunately, the common features observed previously are corrupted in high frequency noise. This is likely caused by smaller pockets of noise being mistaken for the foreground and being caught up when searching for contours causing the estimated area to be inflated.  Inspection of the data showed that the expected behaviour is occurring in the region of 20 pixels squared. When the data is filtered for only the values that are less than or equal to 20 pixels squared, the data becomes a lot clearer.    *Figure 36: Filtered surface area values calculated using the GrabCut algorithm*  As the filtering was applied after inspecting the data, the physical reason for the threshold value is unknown. Some denoising filters that remove the problematic noise could help get to this stage more naturally but that would require further investigation.  The goal with estimating the volume is to estimate the size of the melt pool. The developed thermal camera platform captures information about how the laser’s energy is distributed below the surface. Within this area is the melt pool so estimating the area of the thermal activity will provide an overestimate of the melt pool volume.  The volume estimate is based around an assumption that the laser power is symmetrical across the area. This is backed up by footage recorded by a thermal camera that was connected in parallel to the laser head. This camera recorded the surface radiative heat coming from the build site and provided information on how the laser’s power was distributed on the surface. This footage showed the distribution to have a circular base meaning the power is uniform across the target area.  With this assumption, the 2D data recorded by the thermal camera can be rotated about an axis to form a 3D point cloud from which a shape can be interpolated and volume estimated. As the data is low resolution the 3D interpolation algorithms will struggle to build a shape. As such, it is best to interpolate between the data points to form a more favourable resolution. In addition, an effective interpolation method would provide a means of getting high resolution data from cheap sensors.  First, the minimum bounding box surrounding the area of thermal activity is found to ensure only the data of interest is interpolated. Then only the data on the right half of this box is chosen for interpolation. This is to minimize the amount of memory required for this process as the number of data points generated by the rotation scales rapidly. A Gaussian-based Radial Basis Function is then used to interpolate the target data to twice the resolution. The data is then rotated about the y-axis at 5 degree intervals to form the 3D point cloud representing the heating area. The data is then thresholded for only the temperature values above 15 degrees Celsius to remove background noise. The pipeline is summarized in the following figure.    *Figure 37: Diagram showing the pipeline for estimating the melt pool volume.*  Two 3D interpolation techniques were trialled to test quality and robustness. The data is inherently noisy so interpolation methods may generate spurious artifacts or faces causing the process to fail so robustness is of key interest.   1. The first method trialled is Delaunay Triangulation which attempts to build a surface composed of triangles from the provided data. When the boundary of the heating area was clearer, Delaunay was able to produce clear surfaces with the right shape that was expected. However, it had a tendency to crash repeatedly even on the better frames with a high percentage of the data failing to be processed. 2. The second method trialled was Gaussian Splat which uses a multidimensional Gaussian distribution to interpolate between the point cloud to form a high resolution surface. This tended to over interpolate between the points causing the volume to become inflated. However, this technique proved to be faster and more stable than Delaunay. It should be noted that none of the volumes estimated from these techniques have been verified.     *Figure 38: 3D surface reconstruction using Delaunay Triangulation (left) and Gaussian Splat (right)*    *Figure 39: Estimate of volume using Gaussian Splat for subset of Arrow dataset*   1. A more unusual technique trialled is the Flying Edge algorithm. This is designed to take image data and convert each pixel to a voxel which is a cubic volume of space. The images are now rectangles of unit thickness. Each voxel is colour coded based on their temperature value above 15 degrees Celsius. By stacking these processed images, a visual history of how the shape of the heating area changes over time is formed.     *Figure 40: Image stack formed using Flying Edges algorithm for the upscaled frames 91399 to 150000.*  The surface area of a particular slice can also be estimated from this data to provide another source of information. Rendering this shape requires a lot of memory resources and there is little to be gained by rendering the cooling and pre-build temperatures. The shape is therefore built using only active frames corresponding to when the build was occurring. This approach in conjunction with the other 3D modelling methods outlined previously allow for a historical thermal fingerprint of the build and melt pool. The plot below is the estimated surface area of this data range.    *Figure 41: Estimate surface area of each slice in the Flying Edge render.*   * 1. **Thermal Image Upscaling**   As the resolution of the thermal camera is very low compared to other end cameras there were concerns over the potential lack of detail that would be generated. To combat this, an image interpolation method was investigated and trialled to see if the images can be safely upscaled whilst maintaining the main features. These upscaled images were used to build the render seen above and the same one was used in the surface area estimate.  Like with the point cloud, an interpolation method was trialled to see if valid high resolution data can be obtained. As training a specialised network for thermal images is outside the purview of this project and would require gathering an extensive range of data from a range of thermal cameras, the idea was to see if a pretrained network designed to operate on “normal” images can perform just as well on thermal images. The trialled method is a neural network trained on a range of artistic styles called Waifu2x that is designed to upscale and denoise images. It is a published, well referenced network that has proven to be effective with photo and anime style images.  The objective of the network is to recover the high resolution image from a low resolution. The first stage of the operation is to break the source image into a set of equi-sized regions known as patches that are then broken down into a set of representative features. The second stage is to map these patches to their counterpart in the target high resolution image. The final stage is to aggregate these patches to form the target high resolution image. Waifu2x is a convolutional neural network that performs these steps and has been trained in a supervised fashion to learn the mapping relating the low resolution patches to the high resolution patches. It has been trained on a range of image datasets as no single mapping function can be applied to every type of image as especially artistic images will have vastly different features. Each model is available as a different configuration to use.    *Figure 42: Example of the upscaled results using Waifu2x. The original image (left) is from the first parallel BEAM thermal camera and has been scaled using the anime art style model.*  The network was first evaluated across all trained models, supported scaling factors and denoising factors using the thermal images generated through normalizing the thermal data and converting to an image. The output was converted back to temperature values and compared against the input by looking at the differences in minimum, maximum, mean, range and variance in those factors. The idea was to find the model that least impacted these parameters. In the end it was found that the model trained on realistic Photos performed best. It was not believed that the project generated enough data to retrain the network for this purpose.    *Figure 43: Impact of using the Upconv 7 anime style art RGB model on the maximum temperature at different scaling factors*   * 1. **Unsupervised Thermal Imaging Segmentation**   A number of unsupervised learning techniques were also trialled with the thermal imaging data. The goal was to separate the thermal activity from the background and break it down into further classes ideally containing the defect data in a separate class.  Unsupervised learning refers to a class of algorithms that teaches itself to classify data based on a set of features. The most common application of these techniques is to cluster data into different classes. Regions of multidimensional space that define a class are updated based on the distance between calculated feature values. Once trained, data is assigned to a class based on where it resides in this space. The main advantage with unsupervised learning is that it doesn’t require labelled data. This is especially useful when you don’t have the time to label the data or you don’t know how to label the data. With this project, it is known that any of the sensor platforms could be recording the formation of a defect, but it is not known what form this data would take. Therefore, we can’t appropriately label the data to separate it from background and normal behaviours. Hopefully the appropriate choice of features used in an unsupervised way can be used to build a data pipeline that learns how to classify the data and detect a defect.  Two unsupervised techniques were tested on the thermal camera footage recorded by the developed camera platform during the arrow shape build. The goal was to test different methods to see how they separate / segment non-defect data as well as general performance.   1. The first method was an optimized image processing pipeline designed to label regions of an image. It was originally designed to label active and inactive regions of images of cells. This pipeline has been designed to be used in both an unsupervised and supervised manner. The pipeline first clusters the images into superpixels using the SLIC (Simple Linear Iterative Clustering Technique) technique. This method groups pixels based on a combination of physical distance and color distance. Superpixels are a popular technique for reducing a large image to a smaller, more representative set of regions that can be described by a set of features. This is a more efficient way of processing a large dataset, such as an image, and is closer to how humans perceive images.   The features used to describe the superpixels in this case are a combination of color and texture features and the unique labels of each superpixel. Color is described by a set of statistical metrics including mean and standard deviation. Texture is quantified by the different ways the pixel values change across the space of the image. In this case, it is described by the response to the image being convolved with the kernel filters in the Leung Malik filter bank. The filter bank is generated by an existing open source script. The response to each filter within each cluster is then also described by a set of statistical metrics including mean and standard deviation.    *Figure 44: Example of the thermal image response to the Leung-Malik filter bank. The source image is in the top left and every other image is a response to each of the 48 filters.*  Texture filters that respond to the orientation of subjects in the image are ignored as the cells in the original testing data do not change. This is also the case in the thermal data as the path of the laser always travels the same direction relative to the camera causing the thermal behaviour to distribute towards and outwards towards the bottom of the image. Also the camera is fixed at a set distance and orientation so this optimization is valid for this data. The features are then used to estimate a GMM where the goal is to describe each class as a combination of normal distributions based on the features. This forms a total of approximately 480 features describing each image. The parameters for the distributions are calculated using the EM (Expectation Maximization) algorithm. This is the main learning part of the pipeline and builds a model of each class and can be used to calculate the probability of a given cluster belonging to a given class.  The pipeline takes it a step further by representing each superpixel as a node on a graph with neighbouring relationships based on the difference between clusters. The paper proposes metrics based on distance between superpixel centres, distance between colors, distance between features and distance between the probabilities estimated by the model. For testing the distance between features was used.  The nodes are then separated into groups using a Graph Cutting technique which seeks to separate the nodes into distinct groups or classes based on their relationships. During testing, the regions were separated into three classes; one for the background, one for “normal” activity and one for behaviour that does not fit into the other classes, hopefully the defect behaviour.  The pipeline was able to separate the thermal activity from the background pretty well and place the thermal activity in a separate class. As there is no known defect data, the pipeline has separated the thermal activity in a more and less active class. The boundaries between these classes remained reasonably consistent throughout the dataset and didn’t swap labels    *Figure 45: Example of the output of the unsupervised pipeline. Each color represents a different unique label.*   1. The second technique applied was K-means clustering. This more generalised technique attempts to identify the centres of clusters in a multidimensional feature space. The centres are initially set as random values and the initial labels are which centre the data is closest to. The centres are then updated as the mean value of the data in each class. This process is then repeated until the position of the centres doesn’t change. The output of this algorithm is then the labels using these final centres.   In this case it was used to identify three classes of temperature values. The temperature images are unravelled into a vector of pixels and each pixel was fed in with the temperature being its descriptive feature. The output label vector is reassembled into a label image. Each image was used as an independent piece of data as the implementation used has no memory between iterations. Below are two examples of the labelled output drawn with a fixed colour scheme to show the different classes. A target of three classes was set with the same intentions of separating the activity from the background and hopefully placing the defect data into a separate class.  *Figure 46: Two example label frames from the K-Means classification of thermal camera images. The different colors represent the different classes.*  It can be seen that the laser induced activity was successfully separated from the background noise. However, the class labels were not consistent across all the images likely due to the change in the laser head’s position affecting the magnitude of the temperature. Perhaps the texture features of the built pipeline helped mitigate the changing in identities. As the training routine of K-Means is based on the cluster centres settling at a fixed value, the constant moving of the head and the pulsating of the laser power means a more robust algorithm that can handle gradual changes is likely required to create more stable labelling.  A training pipeline was then created based on the built pipeline and is being trained using the thermal images collected from the arrow shape build. The frames are split into two equal groups with the first half to be used for training and the second half for validation. The order of the training set is shuffled to make the training more robust. The images are not augmented or resized as the thermal images are low resolution so downsizing will likely destroy features and changing the orientation is pointless as all the images are the same orientation.  The data being used for training and validation is the thermal camera footage known to be associated with the arrow shape build, not including the cooling frames as the periods at the start and end for the background temperature and cooling behaviour respectively. This is in total approximately 52,000 frames of data. The pipeline is being trained to separate the data into two classes rather than three to see if it can separate the activity from the background in a stable manner. The purpose is to identify the general features that define the thermal activity. To monitor the evolution of the model, it is currently being saved as an XML model every 1000 frames. As of writing the training has not yet finished and is taking an unexpectedly long time (many weeks, even on a high performance machine), but hopefully the training history will reveal which features are important and which are not for future development.  Below is an example plot showing the history of one of the model parameters varies over time. Each file is a collection of parameters describing the weights, means and covariances of the distributions that describe each feature. A program was created that parses the model file to extract the parameters and plot the history of how they change between files. As there is minimal documentation on the structure of the XML file, it had to be reverse engineered.    *Figure 47: Training history of distribution mean associated with feature 0 for class 0. Feature 0 is the mean color for superpixel 0. The model has been trained for a maximum of 23,000 frames.*    *Figure 48: History of the distribution weights for the trained GMM.*   * 1. **Magnetic Impedance Tomography**   Another system that was discussed and investigated was an in-process magnetic imaging system. As the build is being printed, the system would inspect the forming structure and detect defects as they are forming. Magnetism is already being used to map the internal structure of materials in the form of MRI (Magnetic Resonance Imaging) systems in hospitals to inspect the structure of bodies and MIT (Magnetic Impedance Tomography) for local inspection of bones. Some prototype systems have been designed and built for post build inspection of manufactured objects, but they are very uncommon.  The proposed system would have been a MIT system. It would be composed of an even number of electromagnetic coils equidistantly spaced around a circular area. The coils would have been iterated over in pairs with one coil being excited supplying energy into the area and another reading the response. The difference between the excitation signal and the measurement signal can be used to estimate the value of a material parameter across a region of the measured area. When all the information is combined together, an image is created showing the target parameter varies across the measured area. In the case of a MIT system the target parameter is magnetic impedance. Like with the heat distribution collected by the thermal camera platform, artifacts in the constructed image may indicate the formation of a defect.  An open source library for the required mathematical operations was found and a graphical interface was developed around it to solve and record the results. The interface tool was developed to the point of being able to process artificial data generated by the solving library and store the results in a range of file formats in a multi-threaded fashion. Development was halted at this point until the hardware was purchased, the platform was constructed and integrated into the software. Unfortunately, it was not built due to time constraints in the project and the Coronavirus lockdown preventing essential access to technicians to help with hardware construction. Some hardware was purchased including a Raspberry Pi 4 and some cables. As normally specialist equipment is required for this type of system, the hope was that an equivalent system could be built using cheaper parts such as edge computing platforms.    *Figure 49: Screenshot from a video of the prototype MIT solver interface in use. Each of the windows is a different method attempting to estimate impedance.*   1. **Conclusions and Future Considerations**   The aim set out by this project was to extend existing IoT process monitoring setups within the BEAM machine and perform sensing and analysis of these processes for in-situ control and assess the costs and challenges needed to put forward a future business case around IoT implementation of similar legacy machines. To achieve this a number of work packages (WP) were designed with the objectives of building additional hardware platforms and data analysis pipelines, and provide both online and historical characterisation of the thermal imaging data from the melt pool of the build.  Regarding WP1 and WP2, this can be classified as completed as several platforms have been developed and used to collect information about a build process. These form the data pipeline requested, but it should be noted that further development is required to refine them to make them more user friendly and to improve performance. Any conclusions about appropriate casing and safety measures that need to be taken when handling the hardware can be used to complete platforms that weren’t finished or inform future designs.  The characterisation algorithms developed as part of WP1 and WP2 has provided some insights into the additive manufacturing process. We have been able to demonstrate that the use of cheaper IoT sensors from a range of modalities (thermal, magnetic, weight) can provide useful, real-time process and build data. The developed algorithms for modelling and characterising the melt pool also provide a new source of information in which to track and trace the build and any associated defects or anomalies that may occur.  However, it should be noted that WP2 has been partially hampered due to the limited information collected as a result of limited initial access to the machine and the coronavirus lockdown cutting off access completely. There is a need to gather further build defect data to allow for a more conclusive evaluation of the characterisation methods, however plans are in place to continue further experiments within 2020 when access to the machine allows.  This project has revealed many aspects that should be considered for future projects of a similar nature. First off is the level of access researchers have to the machine of interest. As the environment is often an industrial one, getting access to the machine for an extended period to fit hardware or collect results can be difficult due to the health and safety requirements and level of training required. The training courses needed for researchers to get the same level of access as a regular user may take several months and take up a significant portion of the project schedule. This level of training may also afford users access to information that is stored in otherwise unknown places. The period of access is further limited by lingering health hazards such as the metal powder that can remain in the air after using the BEAM machine. Finally, the target machines are often in constant use meaning scheduling the required time can be difficult with any requests by project researchers being of lower priority.  The next consideration is the unique challenges of the environment and the potential impact on any hardware that may be installed. With the BEAM machine there were concerns over the temperature and stray powder damaging the developed platforms as they have to be positioned close to the build site. This introduced the need for some sort of casing to protect it which increased development costs. For other projects this may also introduce restrictions on the choice of parts due to limited space. The challenges of the installation site may also impact hardware choice or require custom parts to be ordered like the mounting beam for the thermal camera platform.  The final consideration is those using the project outputs after the end of the project. In projects involving an industrial partner, it is often a requirement to develop a product or service that can be used by someone outside of the project. This affects how software is developed and often introduces the need for user interfaces for complex software such as control software. This places a burden on researchers to try and develop software for non-technical users that may not be able to read code or software documentation. It also means users will need to become familiar with using code maintaining services such as GitHub. The scope of this project was mainly research but also KE and in that the need to provide suitable understanding and text for non-technical readers, something which is time-consuming and needs to be factored in with regards to future deliverables on similar projects. | |
| **2. Outputs** | |
| Please provide information on the development of papers, prototypes, products, services, etc.  If you have delivered workshops, facilitated meetings or given presentations, please provide details relating to number of attendees, participants etc. | |
| Over the duration of this project a number of outputs and developments have been created, both to meet the original aims of the project, and as an extension to this with the goal of elucidating other interesting features suitable for process characterisation.   * The first set of outcomes is tied to the four hardware platform prototypes that were developed as part of this project with three of them having been tested in the work environment. Their integration into the work environment, testing and validation has been an insightful help to the technicians working on the LBAM machine as a guide for future work in this area. These prototypes will continue further refinement and development in collaboration with the MAPP Hub and BEAM team, as they have been involved from the start in guiding their development. Further details of their construction, costs and integration can be found on the Github repository that support this project. * In addition to these hardware prototypes are the supporting software and tools developed to run or assist in their function. The software for these platforms and the programs that analyse the data are also stored and documented on the GitHub repository. This includes the model for calculating the laser power density from the radiative heat recorded by the parallel thermal camera, which is built as an importable software package. This package includes the ability to parse the H264 file recorded by the thermal camera. Materials are specified by a set of parameter data points stored in a config file. This allows the users to apply the model to new materials and ultimately for other users of LBAM machines to undertake the work performed in this project. * The ability to parse HDF5 has also been compiled into a standalone GUI (Graphical User Interface) allowing other users to inspect the results without needing to import the model or setup a programming environment, simplifying the process for non-technical users. In preparation for data being collected by the second thermal camera another GUI was developed for inspecting the recording. The results would have been in a CXD file and the GUI provides a means of viewing the data and metadata, this is on hold for the moment but will be finalised and added to the repository at a later date. All software used for analysing the data, generating the results, developed models and 3D renderings are stored in a Github repository. The code is documented through a combination of Markdown files explaining the results and comments in the code itself. * Regarding dissemination of the results and research in this project it can be split into three main areas, the first internal, which takes into account all group and collaborative meetings with MAPP Hub and BEAM machine members / technicians. The second is external and includes presentations of this research outside of our working group, in particular early results have been presented at a recent manufacturing day held in Cambridge, where colleagues on similar projects and SME collaborations were able to present and discuss their individual work and get feedback. Approximately 30 people from a range of different institutions attended this meeting. * The final area is that of future dissemination, where we have looked to target a number of conferences and journals (MAPP conference in January 2021) in which to publish our results, and interested parties (Rolls Royce / Tinsley Bridge) for a KE workshop on this area. Tied to this workshop is the creation of a technical report of the main work and outcomes of this project so as to guide future LBAM users and those seeking to integrate IoT into their manufacturing processes. This is built upon the Github repository documentation and additional personal feedback from all collaborators on this project and is on-going with a date for completion by end of June 2020. Finally, we are also in preparation and ready to submit a EPSRC manufacturing the future research proposal around this theme of additive manufacturing and process control through the use of ‘Edge’ computing, targeting upcoming rounds within 2020. | |
| **3. Outcomes** | |
| Please describe the changes that have occurred as a result of this project. | |
| This project has been able to provide a range of insights into Additive Manufacturing (AM) processes and provide the means to collect data for future insights. The data pipeline developed as part of WP1 has provided a means for technicians to collect a range of data through different sensors. This includes previously difficult to access information such as sub surface power distribution. The more unusual Hall sensor platform also provides new avenues of research as there is not much research surrounding the application of magnetism.  The characterisation algorithms developed as part of WP1 and WP2 have provided some insights into other parts of the additive manufacturing process. We have been able to demonstrate that the use of cheaper IoT sensors from a range of modalities (thermal, magnetic, weight) can provided useful, real-time process and build data. The developed algorithms for modelling and characterising the melt pool also provide a new source of information in which to track and trace the build and any associated defects or anomalies that may occur. It was unfortunate that we were unable to carry out further experimentation and builds as a means to gather data on the quality / outcomes of builds to better tie the developed modelling approaches to real world defects. However, this was mitigated through pushing on with the data we had and arranging access to the BEAM machine at a later date in order to complete this work for upcoming publication / workshop dissemination with partners.  The analysis into the estimated mass flow rate revealed the dynamics of the problematic resonance that currently hamstrung the BEAM machine at the time. Though unverified, the 3D rendering results provide an unusual means of inspecting the thermal history and estimating further forms of characterisation that can be developed further in future projects.  The techniques and methodologies developed throughout this project has helped the researchers involved gain new skills many of which can be applied in other projects. The table below provides a summary of the skills and knowledge gained by the specific researchers.   |  |  | | --- | --- | | **Researcher** | **Knowledge Exchange** | | David Miller (Research Associate) | * Thermal image processing skills and knowledge * Transferrable skills in project management * Better understanding of AM process * Development of image processing skills * Adaptation of technologies * Process of building a data capture pipeline * Learning about 3D rendering and estimation techniques * Improved software skills * Experience packaging software to be imported by other users | | MAPP (Felicity, Lova) | * Better understanding of AM process * Better understanding sensing technologies * Better understanding of how to integrate new technologies into their environment | | ACSE (Michael, Boyang, Divya) | * Management skills * Interpersonal skills * Build on existing partnerships to create new partnerships * Engagement with local businesses * Better understanding of AM process * Better understanding of how to integrate new technologies into new environments. * Adaptation of technologies from other projects * Process of building a data capture pipeline | | Tinsley Bridge | * Application of prototypes and their integration * Lifecycle of hardware / software data pipeline * Scale up of technologies | | Beatson Clark | * Application of thermal imaging skills and technology gained * Better understanding of how to integrate new technologies into their environment | | |
| **4. Impact** | |
| What is the impact of the changes described in section 3? Please discuss the influence or benefit that has occurred outside academia as a result of your project. (On understanding, behaviour, attitudes, decisions, policy, employment, health, wellbeing, prosperity, the environment….) | |
| The thermal technology and skills developed throughout this project have since been applied in another thermal camera project involving the company Beatson Clark. The project involves using an IoT thermal camera platform to monitor the heat distribution in a glass forge. This is similar to the monitoring of the melt pool in a AM process as the heat distribution is key to forming a stable, high quality glass product. This engagement between academic researchers and a local business will hopefully lead to future projects and contribute to the growth of local businesses.  There is an intent to publish the project results in an appropriate conference such as the MAPP Conference which has been delayed to January 2021. There is also an intent to develop one or two journal papers depending on the scope of the papers and further experimentation.  All of the platforms developed as part of this project used IoT and edge computing technologies which are substantially cheaper compared to higher end technologies. For example, the scales being used to estimate the mass flow rate cost approximately £250 and the developed scale platform cost approximately £50 to develop. The other platforms had a similar development cost. The thermal camera platform uses the MLX90640 thermal camera that is available for £54 which is a lot cheaper than a higher end thermal camera such as products from FLIR which at minimum cost several hundred. Despite this, the tested platforms have been shown to collect data with distinct dynamics and features showing that low cost technology can collect useful data. Furthermore, the developed scale platform is saving the BEAM technicians time by removing the need to estimate the mass flow rate at the start and instead continuously log this information for them to a database that can be inspected later. This improves productivity by giving them more time to run experiments. This furthers the case for industry to start using IoT technologies to gain insights into their manufacturing process and also start developing their own platforms.  In addition to the development and acquiring of skills listed in the previous section, this project has provided an opportunity for an early career researcher David Miller. The project was conducted by a mixed team from diverse backgrounds and contained individuals with a wide range of experience varying from minimal experience of an early career researcher to published, managerial level researchers with several year’s experience.  A workshop is organised to share the IoT experience with Tinsley Bridge. Tinsley Bridge is interested about the digital inspection and measurement methods enabled by IoT technique and wish to carry out further research collaboration project not only to adopt the IoT technology for real worl manufacturing process monitor, also trying to development the solution to address more deployment challenge to let the IoT device survive in the crucial industry environment.  Additional benefits and impacts on this project is the gained knowledge and experience has led to the development of a EPSRC manufacturing the future led proposal to be submitted in the upcoming panels of 2020 for this theme. This involves a collaboration across three major universities (Cardiff, Imperial College London, and Sheffield) and multiple industrial partners. | |