Journal of Manufacturing Systems 57 (2020) 31–45

Contents lists available at ScienceDirect

Journal of Manufacturing Systems

journal homepage: www.elsevier.com/locate/jmansys

Review

A review on wire arc additive manufacturing: Monitoring, control and a framework of automated system

Chunyang Xia[a,b], Zengxi Pan[a,*], Joseph Polden[a], Huijun Li[a], Yanling Xu[b], Shanben Chen[b], Yuming Zhang[c]

[a] School of Mechanical, Materials, Mechatronic and Biomedical Engineering, University of Wollongong, Wollongong, NSW, 2522, Australia
[b] School of Materials Science and Engineering, Shanghai Jiao Tong University, Shanghai, 200240, China
[c] Institute for Sustainable Manufacturing and Department of Electrical and Computer Engineering, University of Kentucky, Lexington, KY, 40506, USA

ARTICLE INFO

Keywords:
3D printing
Additive manufacturing
Control
Monitoring
WAAM

ABSTRACT

Wire arc additive manufacturing technology (WAAM) has become a very promising alternative to high-value large metal components in many manufacturing industries. Due to its long process cycle time and arc-based deposition, defect monitoring, process stability and control are critical for the WAAM system to be used in the industry. Although major progress has been made in process development, path slicing and programming, and material analysis, a comprehensive process monitoring, and control system are yet to be developed. This paper aims to provide an in-depth review of sensing and control design suitable for a WAAM system, including technologies developed for the generic Arc Welding process, the Wire Arc Additive Manufacturing process and laser Additive Manufacturing. Particular focus is given to the integration of sensor-based feedback control, and how they could be implemented into the WAAM process to improve its accuracy, reliability, and efficiency. The paper concludes by proposing a framework for sensor-based monitoring and control system for the GMAW based WAAM process. This framework provides a blueprint for the monitoring and control strategies during the WAAM process and aims to identify and reduce defects using information fusion techniques.

1. Introduction

Wire arc additive manufacturing (WAAM) is an emerging technology in advanced fabrication. In contrast to other additive manufacturing (AM) technologies, WAAM makes use of an electric arc as heat-source to deposit metal material layer-by-layer, (as illustrated in Fig. 1) which makes up the final part. According to the type of heat source, WAAM commonly has three types: Gas Tungsten Arc Welding (GTAW)-based, Gas Metal Arc Welding (GMAW)-based and Plasma Arc Welding (PAW)-based. This method of depositing an entire component using weld metal has been in practice since 1925 [7]. Compared to laser additive manufacturing (AM) techniques, WAAM features a number of distinct advantages. Firstly, deposition rates of WAAM processes are typically much higher than laser based AM [8], making WAAM is more appropriate for the production of large scale complex components [9,10]. WAAM also features relatively low equipment costs, as it typically makes use of off-the-shelf industrial robotics and arc-welding equipment. When compared to laser powder AM methods, WAAM also features better material utilization ratio and more environmental-friendly production process [11].

As WAAM technology has a wide range of potential applications across a number of manufacturing sectors, research and development of its general principles has been increasing at rapid rate[1–6], as shown in Fig. 2. Despite this, however, there remain a number of issues that hinder the widespread integration of WAAM into our various manufacturing industries. Harris and Director [12] identified the lack of process robustness, stability and repeatability as the major barriers for the industrial breakthrough of metal AM. This can be largely attributed to the lack of process monitoring and closed loop control of the overall WAAM process. According to a road map workshop on measurement science needs for metal-based AM [13], process monitoring and feedback control for AM process were also identified as key advancements critical to the overall methods' success. As a new emerging technology, those issues also exist in WAAM and the main challenges for application of WAAM can be summarized as manufacturing accuracy, quality assurance and automation level. In traditional welding and AM area, different monitoring method has been tried to improve those issues [14]. The sensing methods mainly include vision sensing, spectral sensing, acoustic sensing and thermal sensing. Different type of sensors feature in different aspects and play various role in process monitoring.

* Corresponding author at: Northfields Ave, Wollongong, NSW, 2522, Australia.
E-mail addresses: zengxi@uow.edu.au, 372538526@qq.com (Z. Pan).

https://doi.org/10.1016/j.jmsy.2020.08.008
Received 11 July 2020; Received in revised form 6 August 2020; Accepted 6 August 2020
0278-6125/

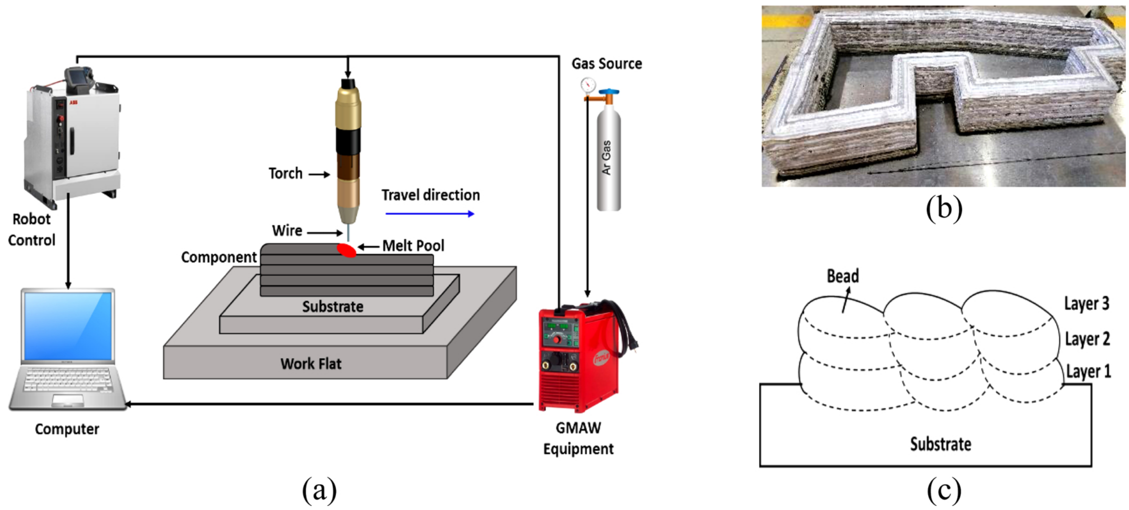

Fig. 1. (a) Schematic of the WAAM system. (b) Photograph of the sample. (c) Schematic of cross sections of the samples.

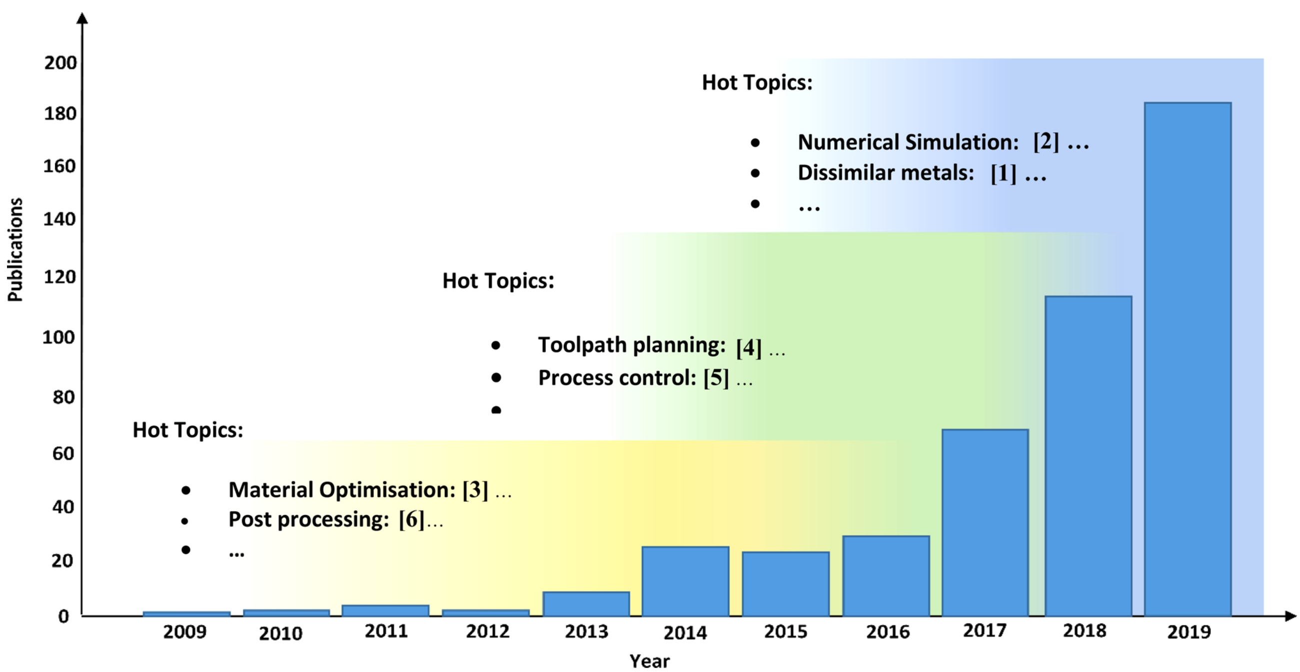

Fig. 2. Publication trend of articles on WAAM.

For example, vision sensors are more applicable to monitor surface object while spectral and acoustic sensing method could be utilized to monitor the internal changes of material. Those research effort will provide reference and inspiration for future research and the development of WAAM.

Although there are numerous research efforts that address the importance of monitoring and control for AM processes, the results and insights produced are still sparse and have not been compiled in a single source. Besides, integrated automated commercial WAAM system is still unavailable. Therefore, in this work, we aim to review current process monitoring and control systems in laser based AM, WAAM and welding areas for future research of WAAM. Furthermore, a framework of automated WAAM system will be proposed based on literature review and our preliminary research work. This study aims to provide inspiration, knowledge, and strategy for WAAM monitoring and control. Laser AM and WAAM both involve metal melting and solidifying, and layer-by-layer deposition process. Therefore, some sensing methods and control strategies used in laser AM could be also adopted in WAAM. For example, the spectral sensing method used in laser AM could be also utilized to monitor the arc spectrum in WAAM. The inspection method for surface defects in laser AM could be also adopted in WAAM. This review could also provide orientation for developing automation systems for other forms of AM.

This paper is organized as follows: Section 2 describes some fundamental hindrances to the general WAAM process. To explore potential solutions to these identified shortcomings, Sections 3 and 4 review literature relating to process monitoring and control in AM. In Section 5, an automatic WAAM system with monitoring and control function is proposed. Section 6 concludes this paper.

2. Challenges and opportunities

As an emerging AM technology, there are still a number of technical challenges for WAAM that need to be overcome to ensure the reliable quality of produced parts. These challenges can be divided into three distinct categories: manufacturing accuracy, quality assurance and

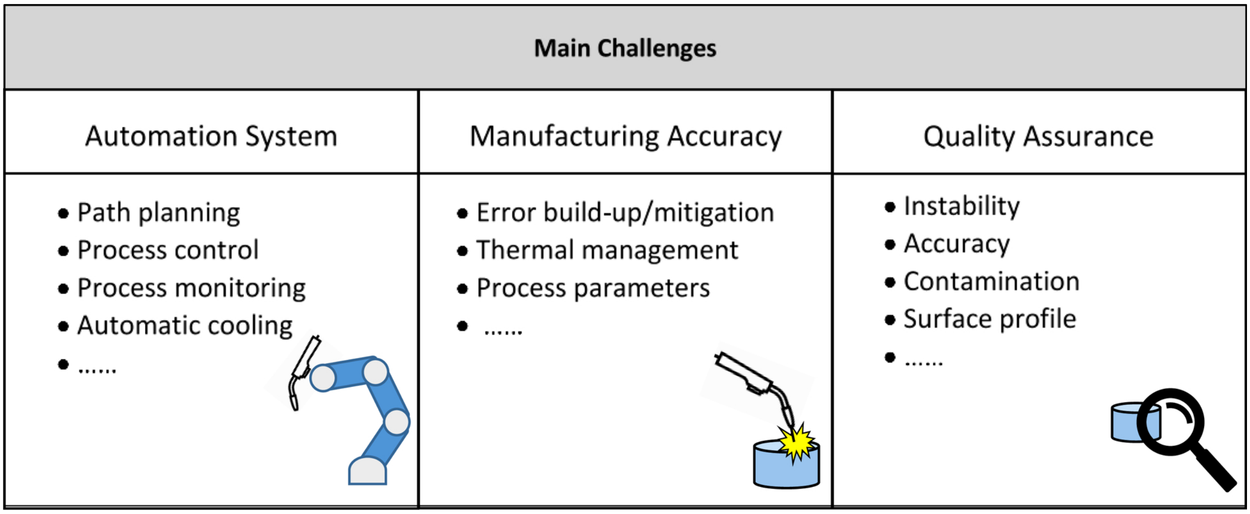

Fig. 3. summary of challenges to the overall WAAM process.

automation system, as shown in Fig. 3 below. The remainder of this chapter aims to explore these three categories further by identifying the core issues at hand, and discussing commonalities between them.

2.1. *Manufacturing accuracy*

The arc-welding process at the heart of WAAM technologies has specific limits to the level of accuracy achievable in the deposition process. For example, the accuracy of a deposited component is limited by the diameter of the wire used. Arc ignition and extinguishment processes also lead to significant fluctuations in deposited bead geometries. Inappropriate selection of welding process parameters can also affect the geometric accuracy of deposited components. Distortion caused by heat accumulation [15] and the resultant shrinkage during cooling [16] also make it difficult to control the accuracy of the deposition. Compounding all this is the ‘staircase effect’, wherein small geometric errors in each deposited layer accumulate over the multi-layer build process, further accentuating the negative effect of these errors [17].

Researchers have developed bead geometry prediction models to address issues relating to deposition accuracy. These models assist in the selection of appropriate process parameters and are also employed in planning tool paths for the deposition process [18]. Xiong et al. [19] used neural network and second-order regression to model the relationship between a suite of process variables and the resultant bead geometry for WAAM. Nagesh and Datta [20] utilized a Back Propagation (BP) neural network model for estimating bead geometry for TIG welding processes. It must be noted that these approaches operate in an offline manner, making use of static training data. However, in contrast to this, the WAAM process is a time varying system due to factors such as heat accumulation and varying boundary conditions. As the number of deposited layers increase, it is inevitable that the prediction model will begin to skew from the physical process (see ‘staircase effect’ [17]).

To overcome this, it is necessary to build an online learning adaptive model which makes use of temperature build up as an input. As a result, different sensors, including geometry measuring sensors and temperature sensors should be integrated to WAAM system to monitor this process. Furthermore, closed-loop control should be implement to guarantee the accuracy and stability in WAAM process.

2.2. *Quality assurance*

The reliable production of parts to requisite standards of quality is critical to the uptake of WAAM in modern manufacturing. In the context of this work, we are particularly interested in the detection and mitigation of welding related defects which occur during the WAAM process.

WAAM shares a suite commonalities between both laser AM and arc welding processes. In the context of this section, these commonalities concern the generalized fabrication procedure along with the metal remelting and bonding process. Arc welding and WAAM share the utilization of an electric arc as the primary heat source, thus they both share a number of common or similar defects. Laser AM and WAAM share a similar build procedure, so defects relating to the layer-by-layer build process are common to both. With this in mind, we can look to established quality assurance methods used in both laser AM and arc-welding processes for inspiration which can be applied to WAAM.

These commonalities are represented in Fig. 4, below. Defects common to all three processes include porosity, void and crack formation. Those defects result from an array of factors, including raw contamination, poor process parameters, environmental disturbance and process instability. The presence of these defects results in abnormalities in certain process signals, such as visual, spectral and electrical responses. Through careful online monitoring these signals, it is possible to identify these corresponding defects. These concepts are explored further in Section 3.

2.3. *Automation system*

Compared to Laser based AM, WAAM still lacks a suite of integrated equipment, and there is still no commercial WAAM system available on the market. WAAM based manufacturing is still, for the most part, carried out in a lab-type environment, by people who are experts in the various intricacies of the process. Different parts are built up with different parameter sets, carefully selected by the operator in order to generate the final part. This indicates that significant improvements to the automation systems which carry out the WAAM process remain to be developed. At present, the WAAM process still requires a large amount of human involvement, such as the pause/resume commands during cooling phases. Additionally, adjustments to the tool path and process parameters also generally rely on human intervention during the build process, all of which rely heavily on the experience and knowledge of the operator overseeing the build process.

In order to extend the application of WAAM in industry, it is necessary to improve levels of automation. To achieve this aim, real time process monitoring during WAAM is essential, including visual signal, electrical signal and so on. Furthermore, based on those signals, process control and decision making algorithm should be developed to control and optimize the process.

We should also discuss the software development for WAAM.

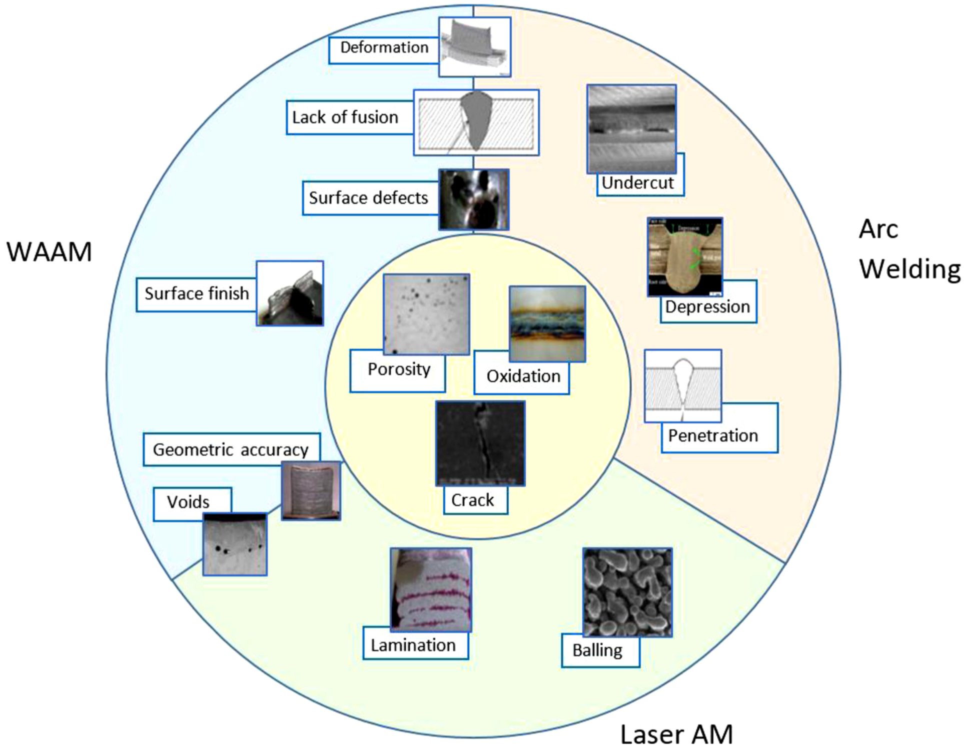

Fig. 4. Defects in WAAM, Laser AM and arc welding.

Software is critical, and also provides the backbone for automation and process monitoring. Not many commercial software options for WAAM are mature. Automated robotic welding (generic welding, not WAAM) solutions are now only just becoming more common in industry, after years of software development. A heavy focus on software development is key in integrating the ideas brought forward in this work into real world WAAM solutions.

2.4. Opportunities

As addressed above, the main challenges for WAAM mainly include manufacturing accuracy, quality assurance and demand for automation system. At the same time, there are also opportunities for the development of WAAM with the concept of Industry 4.0 being put forward.

The concept of Industry 4.0 was proposed for the fourth industrial revolution, which addressed the integration of automation, cloud computing, Big Data and Internet of Thing (IoT) in modern manufacturing industry. Haleem and Javaid [21] proposed that Additive manufacturing and robots are essential parts of the CPS-based manufacturing systems of Industry 4.0. As asserted by Dilberoglu et al. [22], with the development of Industry 4.0, additive manufacturing technology will be widely used to produce small batches of customized products that offer construction advantages, such as complicated, lightweight designs. Efficient additive manufacturing systems will reduce transport distances and stock on hand. At the same time, the advanced information technologies in industry 4.0 could also promote the development of AM. The concept of Internet of Thing could help to realize the unmanned workshops for WAAM and the manpower can be saved efficiently. The concept of Big Data will help to realize the data sharing and processing, which could improve the CAD design, process optimization, and quality control for WAAM.

Furthermore, the emergence of Artificial Intelligence (AI) technology will also promote the development of WAAM. Some scholars have proposed to apply AI in WAAM. For example, Wang et al. [23] proposed to utilize a convolutional neural network to predict the future images of welding pool during WAAM process, and the weld reinforcement was predicted by a regression network. Nguyen et al. [24] applied an artificial neural network in path planning to determine characteristic distance. Deng et al. [25] proposed to use XGBoost algorithm to predict the bead geometry in WAAM. Tang et al. [26] applied deep learning algorithms to categorize the surface image of WAAM, and the surface defects can be inspected.

3. Sensing methods in AM

To improve WAAM we must monitor various data produced during

Table 1
Monitoring method of different defects.

Objectives	Vision	Spectrum	Acoustic	Electric	Thermal	Formation reason
Porosity & Void	[27]	[28–30]	[31–33]	[34–36]	[27,37]	• Raw material contamination • Unstable process • Poor process parameters
Crack	[38–40]	[41,42]	[40–44]	[45]	[39,46]	• High heat input and high cooling rate • Poor process parameters • Large stress
Surface defect	[26]	[47–49]		[50]	[46]	• Poor process parameters • Lack of protective gas
Melt pool dynamic	[51,52]	[53]	[54,55]	[56,57]	[58,59]	

the process, with particular attention to variables that affect the quality of deposited weld-material. As shown in Table 1, there are significant efforts being made by researchers to correlate various process data for the quality of built layers. Visual data, along with temperature, spectral and acoustical signals, amongst others, form particular focal areas of this work. In the following section, an overview of the main monitoring technologies used in AM and related fields will be provided.

3.1. Vision sensing

Vision sensing is the most direct sensing method, it is useful for analysis of melt pool dynamics and layer/surface morphology. Furthermore, through monitoring by visual sensor, information for use in feedback control, such as melt pool width, height and morphology, can be obtained in real-time. With the development of computer vision technology, a wide range of studies have focused on the acquisition of visual information during manufacturing process.

In the distinct field of laser AM, visual sensing has played an important role. Davis and Shin [60] utilized CCD camera and line laser to monitor the bead profile during a laser cladding process. Line detection and spur trimming algorithms are used to extract the required data. This method is able to obtain bead width and height, which could be used to optimize process parameters in the next layer. For feedback control, however this sensing method may not be suitable due to relatively high processing times causing a lag effect. In another research [61], it was shown that the final quality of AM components is related to dynamic effects in the melt pool. Visual sensing also offers a method to acquire these dynamic properties and hence offer another level of control over the deposition process. Clijsters et al. [62] developed an optical system, which consisted of high-speed near-infrared (NIR) thermal CMOS camera and a photodiode to monitor the melt pool. The CMOS camera is capable of obtaining geometry of the molten pool, and the photodiode is used to get the molten pool size. The data is processed by "mapping algorithm" to provide an indication of the products final quality.

Spatter is another process signature analysed during laser AM process. Measuring spatter levels can be useful in that they can reflect the overall process stability. Thus, some vision based sensing methods were developed to monitor spatter in laser AM process. As illustrated in Fig. 5, Repossini et al. [63] utilized high-speed camera to capture the image of spatter produced in laser powder bed fusion (LPBF) process. Through feature extraction and data mining approach for image, various melting conditions can be diagnosed during LPBF processes. Furthermore, Grasso et al. [64] developed an in situ monitoring system for SLM process based on capturing infrared images of the process plume. Through methods of machine learning, unstable melting conditions can be detected. Zhang et al. [65] captured the image of melt pool, plume and spatter levels produced in laser powder-bed fusion AM using a single high-speed camera. Key features of these datasets were extracted and used as inputs for Support Vector Machine (SVM) and convolutional neural network (CNN) classifiers. Three distinct levels of product quality were then identified through the resultant models.

Visual monitoring of the deposited surface is a method also employed by researchers. Surface features can be linked to the discontinuities or defects in the final component. In the research by Gobert et al. [66], multiple surface images were collected at each layer during laser AM using a high resolution digital single-lens reflex (DSLR) camera. For each neighborhood in the resulting layer wise image stack, multidimensional visual features were extracted and evaluated using binary classification techniques. Through binary classification, neighborhoods are then categorized as either a flaw, i.e. an undesirable interruption in the typical structure of the material, or a nominal build condition.

In WAAM applications, visual sensing methods were also applied to monitor the defects and process stability widely. Monitored objects consist of melt pool, wire position, arc length and bead surface morphology etc., which can help further advance the development of AM process monitoring techniques. For WAAM system, the wire-feeding direction and position plays a vital role in getting a stable deposition process and smooth weld bead by resulting in different droplet transfer modes. However, significant deviations between the expected wire-feeding position and arc length occur in reality. Zhan et al. [67] developed a camera based wire-feeding position online monitoring and correction system for a plasma based WAAM. Adaptive threshold and Hough transform were used to extract the wire edges and merge the coincident lines, and Radon transform was applied to measure the wire deflection. Bonaccorso et al. [68] proposed a method combining an image processing-based method and arc voltage measurement to control the arc length during the GTAW based WAAM process. Tang et al. [26] attempted to detect surface layer defects during WAAM process, where a camera was used to obtain the image of the deposition surface in real time. Deep learning algorithms and SVM (as shown in Fig. 6) were used to classify different surface defects, which were normal, pore, hump, depression and undercut. A high classify accuracy was obtained.

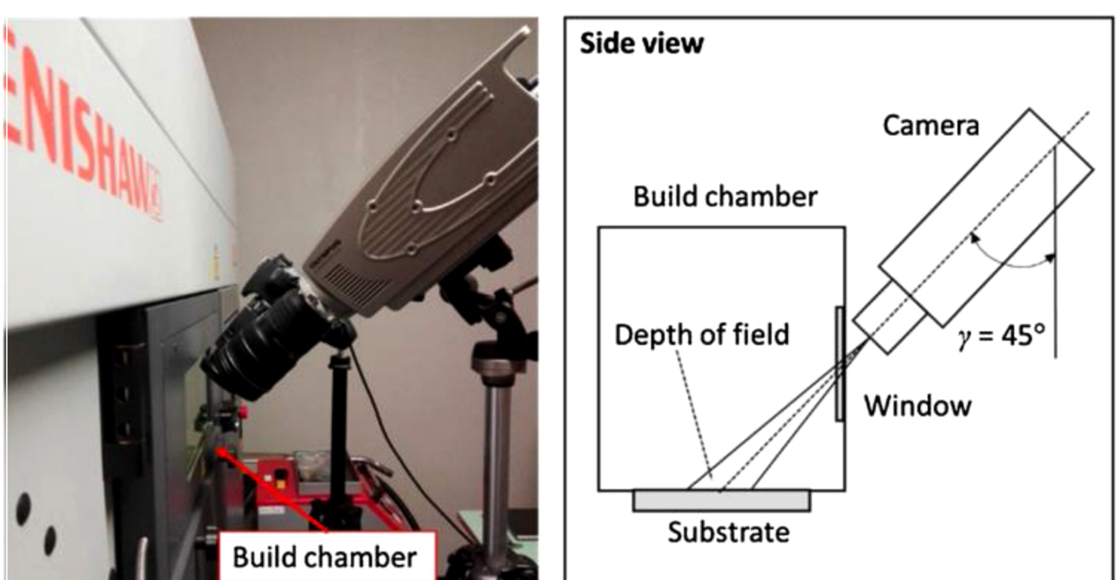

Fig. 5. High-speed camera for laser AM process monitoring.

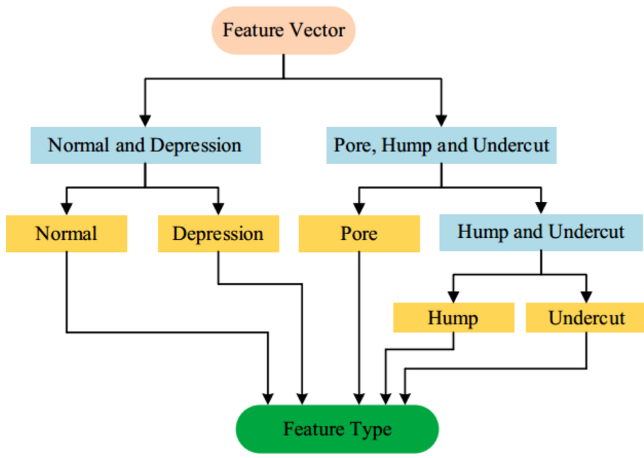

Fig. 6. Structure of binary tree of SVM method.

3.2. Spectral sensing

Optical emission spectroscopy is an effective tool for composition analysis since elemental information is imbedded in spectral signals, which has been used to better understand physical mechanisms and also monitor conditions during processing. For laser AM, Beyer et al. [69] utilized optical emission spectroscopy to identify phase transformation during laser AM processing. It was reported in their research that the phase transformation can affect the characteristics of laser induced plasma during a direct laser material synthesis process. Through monitoring the spectral signal of plasma, the phase transformation can be diagnosed online. By using a spectrometer to monitor laser induced plasma, and through training support vector regression (SVR) with two feature of plasma spectral signal [70], Al concentration can be measured online during laser additive manufacturing of Ti-Al binary alloying process. Ya et al. [71] tried to obtain the temperature of electrons by collecting the spectral signal produced in a laser AM process. The electron temperature and intensity ratio of the spectral signal was calculated and used to indicate the onset of metallic bonding and extent of dilution during a given deposition process.

In WAAM applications, the spectrum produced from arc-welding tasks contains a wide array of information, include metal vapors, shielding gases and arc gases. Therefore, it can be intrinsically linked to defects in the WAAM process. This makes it a particularly promising method for online defect detection. As shown in Fig. 7, based on spectroscopy signal monitoring, Zhang et al. [47] found that welding perturbations and defects during GTAW process can be diagnosed. Huang et al. [29] utilized a portable spectrometer to obtain spectral signals in the GTAW of aluminum alloys. An improved SVM classification model with genetic algorithm (GA) optimization was developed to guarantee accurate estimation of different types of porosity defects.

3.3. Acoustic sensing

Acoustic sensors can provide many advantages in the monitoring of AM process since they are non-contact, non-destructive, and flexible. Recorded acoustic emissions (AE) from a welding process has been shown to produce insights into properties contained within the interior of the materials being welded, such as defect-related information like cracks and porosity. For example, Gaja and Liou [72] used an AE sensor to monitor a laser deposition process. It was found that defects such as cracks and pores occurring during this process could be diagnosed by K-means clustering and principal component analysis (PCA) of the obtained signal data. As illustrated in Fig. 8, Shevchik et al. [73] developed a method of AE sensing for in situ quality monitoring during the laser powder-bed AM process. A Fiber Bragg grating (FBG) sensor, which can provide high sensitivity signal detection, was mounted directly inside the process chamber, ~200 mm from the processing zone. A CNN classifier was developed to process these AE signals, and characterize porosity concentrations during the process. Ye et al. [74] used a microphone to receive an AE signal produced by a Laser melting process. This signal is classified by a deep belief network (DBN) into five melted states. Wang et al. [75] employed the use of AE testing for crack detection during powder directed energy deposition process. With information relating to the speed of the AE signals, and the time taken for the acoustic sensors to receive/process them, the position of cracks created during the process, and propagation direction, can be established.

For WAAM applications, AE signals could be used to infer the arc condition, melt pool dynamics and material internal change. Many factors in a typical WAAM process are can be related back to a characteristic AE signal, including process parameters, variation of welding arc, droplets transitional mode and so on. Pal et al. [76,77] found AE signals are a good indicator of droplet transfer mode and defects during arc welding process. Bhattacharya et al. [78] used an AE sensor, along with Hall-effect current sensor and voltage sensor, to monitor an arc welding deposition process. An artificial neural network (ANN) model with three inputs (current, voltage and sound kurtosis) was built to predict the deposition efficiency. Saad et al. [79] analyzed the relationships between an AE signal and the modes (keyhole mode and cutting mode) of the welding pool in plasma welding process. In this work, a Welch power spectral density (PSD) estimate is used for preprocessing the AE data, and it was found that keyhole mode and cutting mode during the welding process can be distinguished through an ANN model. Chen and Chen [80] applied a weighted mean method to estimate the arc length from welding voltage and sound intensity. Van Bohemen et al. [81] demonstrated that martensite formation during GTAW of steel 42CrMo4 can be recognized by monitoring AE signal. It was found that a certain relationships exists between the root mean square (RMS) value of the measured AE, and the volume rate of the martensite formation during GTAW. Sumesh et al. [82] used a microphone to monitor the acoustic signal generated during welding process. The machine learning algorithms, named J48 and random forest, were applied to identify the good weld, weld with lack of fusion and burn through. In the field of ultrasonic techniques, Rieder et al. [33] conducted online ultrasonic measurement during AM process, and found it is potentially able to indicate qualitative evaluation of residual stresses and porosity. Slotwinski and Garboczi [32] developed an ultrasonic sensor for detecting changes in porosity in metal parts during fabrication on a metal powder bed fusion system.

There are many successful research publications into AE sensing in Laser AM and traditional GMAW applications. But none or not many in WAAM. There is high potential in this area, but researchers have not investigated this in-depth yet.

3.4. Thermal sensing

The principle behind thermography is based on the difference in thermal behavior between the internal structure of the examined object and its flaws. Variations in thermal profile locally or differences in thermal behaviour over time, present a material processing challenge as these can cause different phases and microstructures to develop within the build, leading to inhomogeneous material properties. Thermography is a rapid method as compared to other NDT techniques, such as ultrasonic, for the examination of parts where surface contact or access is difficult. It is easily able to monitor the process during manufacture, allowing for fast results. Mireles et al. [37] developed an infrared thermography system for AM monitoring. Results from layerwise thermography were compared with results obtained using computer tomography (CT) scanning techniques and found the thermographs provide a good indication of defects. Krauss et al. [83] implemented the use of infrared camera to track the process of solidification and quality of powder layer in SLM (selective laser

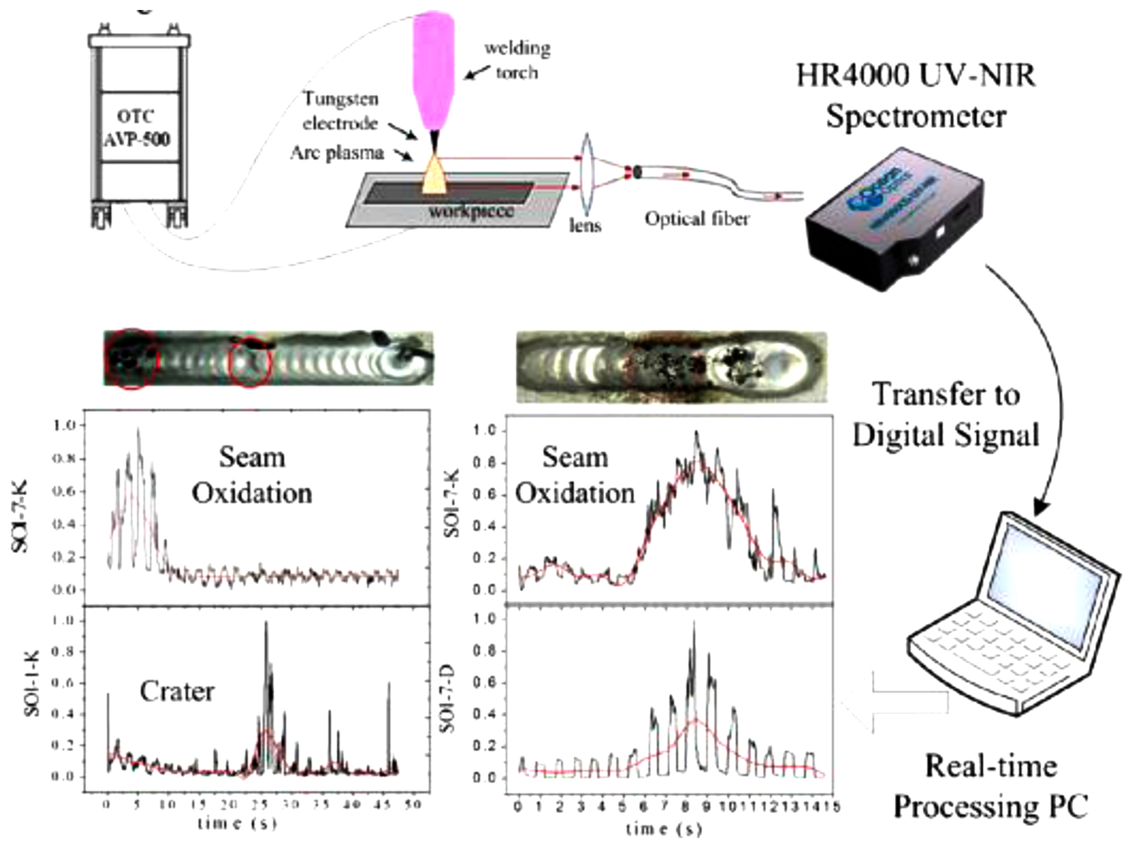

Fig. 7. Diagram of spectrum monitor system.

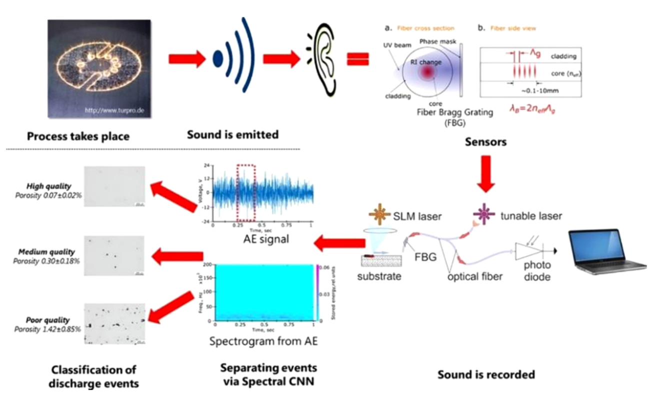

Fig. 8. Diagram of acoustic in situ monitoring system for laser AM.

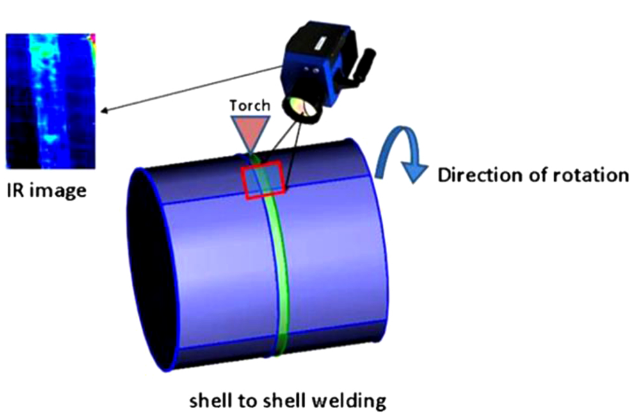

Fig. 9. Schematic diagram of thermal monitoring system.

melting). With this approach, variations in powder layer thickness and a range of flaws were detectable during deposition. Sreedhar et al. [27] developed a thermal image based online monitoring system (shown in Fig. 9) for GTAW process. They found that thermal images from defect-free and defective sectors show statistically distinct features for a simple threshold-based processing. Khanzadeh et al. [84] utilized a pyrometer and thermal camera to monitor the melt pool thermal profile during a laser AM process. Self-organizing maps (SOM) were applied to analyse the 2D melt pool dataset. With properly selected SOM data, the proposed method was found to identify and predict the location of generated porosity almost 85 % of the time.

3.5. Section summary

From the introduction above, it can be seem that a wide range of sensors can be used to monitor the AM process according to the various application occasions. Generally, visual sensor is more applicable to monitor the surface defects and measure the geometrical deviation for feedback control. It has the advantages of rich information and high accuracy. The drawback of visual sensor is that the information in images may be blocked by the strong arc if the arc is not filtered out efficiently. Spectral and acoustic sensors are applicable to detect the internal defects, like pores and cracks. Spectral sensor has the advantages of high sensitivity and rich information. However, its limitation is the obtained information is not intuitive, so its prediction results highly rely on the of data processing and analysis algorithm. Acoustic sensors can also be used to monitor the stability of arc and the mode of droplet transition. However, it is vulnerable to the external disturbance, such as environment noise and most of the acoustic information is correlated to the welding electrical signals which can be easily collected from the welding machine. Thermal sensor is capable of collecting the thermal history of the component through capturing the distribution of temperature. It has the advantages of high robustness, while its

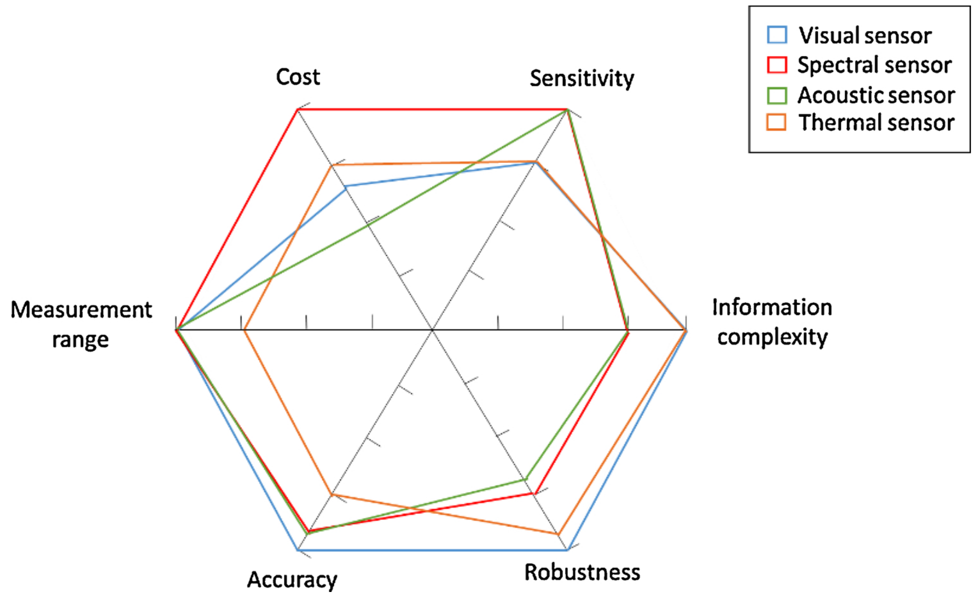

Fig. 10. Features of sensor for WAAM.

disadvantage is that its accuracy highly rely on the reflection coefficient that set by users. Fig. 10 summarizes the characters of the different sensors used in AM.

4. Control strategies in AM

As reported by a roadmap workshop on measurement science needs for the metal-based AM technologies [85], feedback control systems for additive manufacturing are identified as a critical step in manufacturing industry. During deposition process, when the number of the deposited layers increases, it will be hard to control both the morphology and size of a deposited layer, which will affect the geometrical accuracy. The shape of beads can't be easily controlled because of the heat accumulation, especially when the melt pool is situated at the boundary of the deposited layer. Thus, in-the-loop feedback control of the overall process plays a critical role in ensuring reliable production for WAAM.

Table 2 summarizes a literature review on work done in this type of control in AM applications. These control systems typically focus on layer height, width and temperature of the melt pool. Advanced control strategies like adaptive control, predictive control and intelligent control algorithm were utilized to achieve closed-loop control. In this section, we will review and discuss this work in Laser AM and WAAM.

4.1. Laser AM process control

For laser AM, when compared to WAAM, a large number of research in process control has been conducted. A review of literature reveals this body of work predominantly focuses on geometric and thermal control methodologies. Han and Jafari [102] designed a coordination-control scheme that can ensure uniform bead geometry and deposition accuracy in a laser AM process. To do this, material flow was regulated to match the relative changes in speed between the deposition-head and work piece in real time. In the research by Hu and Kovacevic [103], a high frame-rate (up to 800 frames/s) camera was installed coaxially on the top of the laser-nozzle setup to acquire infrared images of the molten pool real-time. From those images, dimensions of the melt pool can be measured to implement feedback control. Hofman et al. [97] used a CMOS camera to obtain the width of the melt pool during a laser AM process, and a PI controller was then used to control the pools width during deposition. Cao and Ayalew [104] proposed a control-oriented multiple input multiple output (MIMO) model for a class of laser aided powder deposition (LAPD) processes. The MIMO model is derived in Hammerstein form by combining linearized dynamics coupled with nonlinear relationships derived from mass and heat balance considerations. This inputs to this model were laser power and scanning speed, whilst layer height and molten pool temperature as were given as outputs. Zeinali and Khajepour [93] used a CCD camera to obtain

Table 2
Summary of process control research in AM.

Process method	Control object	Process method	Manipulated Variables	Sensing method	Control strategy	Reference
WAAM	Layer height	WAAM	WFS	CCD	Adaptive control	[86]
	Layer width	WAAM	WFS	Laser scanner	Internal model control	[87,88]
		WAAM	Travel speed	CCD	Neural self-learning control	[89]
Laser AM	Layer height	Laser AM	WFS	CMOS Camera	Iterative learning control	[90,91]
		Laser AM	Travel speed	CCD	Inverse ANFIS model based control	[92]
		Laser AM	Travel speed	CCD	Adaptive Sliding Mode control	[93,94]
		Laser AM	Laser power	CCD	Fuzzy-PID	[95]
		Laser AM	Laser power	CCD & Pyrometer	Generalized Predictive control	[96]
	Layer width	Laser AM	Laser power	CMOS	PI	[97]
	Melt pool temperature	Laser AM	Laser power	Pyrometer	PID	[98]
		Laser AM	Laser power	Thermal camera	PI	[94]
		Laser AM	Laser power	Pyrometer	Adaptive fuzzy sliding-mode	[99]
		Laser AM	Laser power	CCD & Pyrometer	Predictive control	[96]
	Tool distance	Laser AM	WFS	Resistance sensor	Iterative learning control	[100,101]

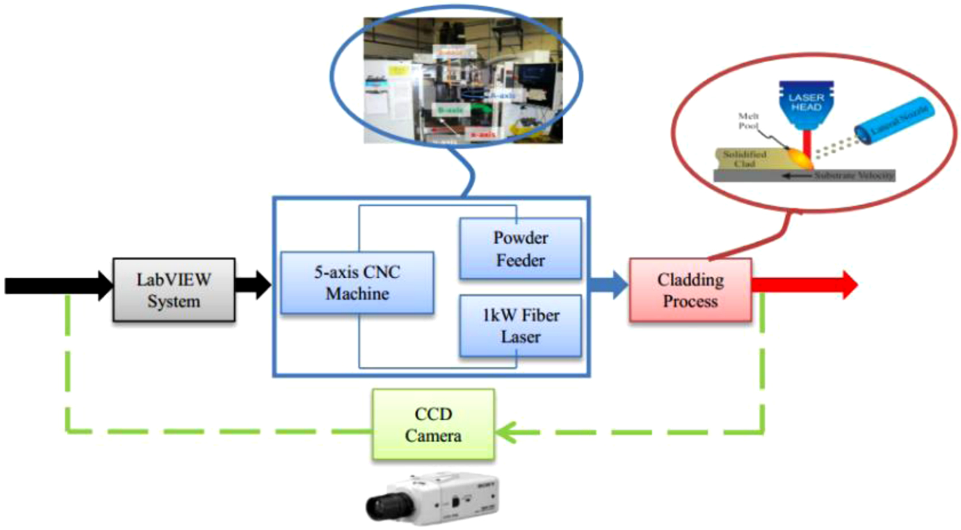

Fig. 11. Laser cladding experimental setup.

molten pool height (shown in Fig. 11) and realize feedback control in laser cladding process. An adaptive sliding mode control algorithm with an uncertainty estimator was developed to control the clad height, and the performance of controller was validated through a number of experiments.

Heralić et al. [90,91] used a 3D scan sensor to get the height profile during a laser-wire AM process. Through a method of Iterative Learning Control (ILC), the deviations in deposited layer heights could be compensated for by controlling the wire feed rate on next deposition layer. This feedforwards control strategy utilized a PI controller to control the bead width through modifying the laser power. In a similar approach, Hagqvist et al. [100] measured the distance between the tool and the work piece by measuring resistance between nozzle and substrate during laser-wire AM processes, and feedforward control was used to flatten the upcoming layer in the deposition process. A second order ICL algorithm was used to determining the wire feed rate.

Song et al. [96] designed a hybrid control system to for adjusting deposition height and molten pool temperature. They designed a master-slave type control scheme; the master height controller and slave temperature controller. This configuration means the temperature controller will be disabled when the deposition height is above a certain preset value. The height controller is a simple rule-based controller and the temperature controller applied a generalized predictive control algorithm. Generalized predictive control takes both feed-forward and feedback signals into the control action to improve performance. This hybrid control system was able to stabilize layer growth by avoiding over-building and compensating under-building through control of the process heat input. Wang and Chen [105] proposed to use fractional-order repetitive control (RC) to advance the quality of laser based AM. In this work, three RC designs were proposed to address fractional-order repetitive processes. In particular, a new multirate RC was developed and found to provide superior performance gains by generating high-gain control at the fundamental and harmonic frequencies of exogenous signals. Experimentation was conducted to validate the effectiveness of this approach.

For conventional control methods, the effect of control algorithm highly relies on the accuracy of the mathematical model of the system dynamic. However, since typical AM processes are complex and nonlinear, and process variables couple with each other, it proves quite a difficult task to develop an accurate mathematical model. Nowadays, intelligent control algorithms are being developed to control such complicated systems with uncertain mathematical models and highly nonlinear task requirements. In previous literature, intelligent control algorithms have been utilized for AM process control. For example, Hua and Choi [95] developed a fuzzy logic-based PID controller to track reference heights through varying laser power during a laser deposition process. Fuzzy logic-based control doesn't require an accurate mathematical model, but it demands knowledge and experience. With this in mind, PID parameters could be tuned adaptively to deal with a time varying system by way of fuzzy logic. In the works by Zeinali and Khajepour [101], a fuzzy logic-based dynamic model was developed for a laser cladding process. In this work dynamics relating to scanning speed and layer height was modeled. A fuzzy modelling approach was used, and some model parameters were estimated online to deal with uncertainties. This online learning approach provided adaption for the real-time control applications. Farshidianfar et al. [92] used Adaptive neuro-fuzzy inference systems (ANFIS) algorithm to model and control the clad height in a laser cladding process. A CCD camera was used to measure the real-time clad height, whilst scanning speed was used as the control action. Renken et al. [106] proposed a learning based control scheme for laser additive manufacturing. In this control approach, an adaptive self-learning strategy was used, which aimed to maintain the stability of the process by updating the parameters of the multidimensional model to restrain environmental influences during the process. Data from an RGB sensor was used to correlate the molten pool size (height and width) with temperature (intensity of RGB signals). Polynomials and radial basis functions (RBF) were implemented into the real-time model, which allowed upcoming data to be integrated into the calculation of updated model parameters.

During the AM process, the temperature of the melt pool typically varies due to heat accumulation in the substrate, which can lead to defects such as non-uniform microstructure, increased heat affect zone, cracking and so on. This makes it important to actively regulate heat input in order to control temperatures in the melt pool. Tang and Landers [107] proposed a layer-to-layer temperature control strategy, where the laser power profile is adjusted between deposited layers. Layer height and temperature are measured in real-time and are then used to estimate the parameters of process physical model through a PSO-based system identification program online. With the model and desired temperature, the laser profile for the next layer could be calculated through iterative learning algorithm. Sammons et al. [108] proposed to use Iterative Learning Control (ICL) algorithm to develop a feed-forward method of adaptive control for the morphology of the melt pool. Tang and Landers [109] utilized Internal Model Principle to design a temperature controller for laser metal deposition. This empirical process model describes the relation between the temperature, and laser power, powder flow rate and traverse speed. The controller able to track the time varying reference temperature effectively. In order to control the molten pool temperature during laser AM, Devesse et al. [94,110] designed a controller consisting of a linear state feedback controller and PI controller. The state space equation was deduced from the physical heat conduction model of the melt pool dynamics. The temperature of molten pool was measured by a hyperspectral camera. A hardware-in-the-loop (HIL) system was built to enable safe and cost-effective testing of the controller in different simulation environments. In order to control the heat input into the cladding layer and substrate, Salehi and Brandt [98] designed a PID controller to control the temperature of the molten pool. A second order transfer function for the laser cladding process was generated through step response experiments. Through validation of experiments, it was found that the controlled temperature of the molten pool was able to facilitate a reduction in the amount of porosity. A more uniform and smaller HAZ, as well as lower dilution, was obtained (relative to the uncontrolled cladding layer). Bi et al. [111] achieved closed-loop control based on infra temperature signal during a laser powder deposition process, constant set-values and path-dependent set-values control were tested and compared. It was found that the process control with a path-dependent set-value can notably improve the homogeneity of the microstructure and mechanical property, as well as the dimensional accuracy of the deposited components. Farshidianfar et al. [112] utilized an infrared camera to monitor surface temperatures during the AM process as feedback signals, and a novel PID controller was established to control the cooling rate.

4.2. WAAM process control

In more recent years, work relating to feedback control systems specifically for WAAM is beginning to emerge. Examples of this include, Xiong and Zhang [86], where an adaptive layer height controller for GMAW based WAAM process was developed. A passive visual sensing system was developed to measure the nozzle to top surface distance (NTSD) as a feedback signal. After approximating the controlled process into a linear system, an adaptive controller was proposed to keep the NTSD constant through adjust wire-feed speed online. In this same work, a neural self-learning PSD controller for bead width was also developed.

During the WAAM process, the welding robot has to decelerate at sharp corners to satisfy dynamic constrains. This can result in over-fill if the wire-feed rate is kept constant. To solve this problem, Li et al. [113] proposed an adaptive process control scheme (APCS) to maintain a uniform bead geometry. The APCS dynamically selects appropriate wire-feed rates according to the dynamic constraint at different sections of the required welding tool path. As this approach is an open-loop control system, high accuracy modelling of the process is required. Doumanidis and Kwak [87,88,114] used a laser scanner and thermal camera to monitor the bead and implemented closed loop control in GMAW based WAAM. To compensate for measurement delays, real-time prediction by a deposition model is employed.

As WAAM features many similarities to the more general field of arc welding technology, we are able to also look into this well-established field of research for inspiration as well. Smith et al. [115] implemented feedback control during GTAW of Inconel 718. A CCD camera was used to obtain the image of the molten pool surface, the width of the melt pool was measured and used as a feedback signal to control the weld process. Fan et al. [116] developed a pinot infrared sensing system to monitor the temperature directly surrounding the melt pool during an arc welding process. In this method, the measured temperature signal was utilized as feedback to control welding penetration. As arc welding is typically a complex, time-variant, process, advanced control algorithm should be developed. Liu and Zhang [117,118] designed a model predictive controller for arc welding processes to control the penetration or weld pool geometry.

There is a lot of Laser AM control systems as it has been researched much more. It is apparent that from this literature review that WAAM is still an emerging process, and these types of control architecture and research etc. is critical to bringing it more to an industry solution. Therefore, a framework of automatic WAAM system was proposed based on literature review. The proposed automatic WAAM system consists of two modules: multiple sensor monitoring module and controller module. The proposed framework can help push forward the development of WAAM in both research and industry.

4.3. Section summary

This section reviews the research effort of process control in both laser AM and WAAM. It can be seen that the research mainly concentrate on laser AM process control, while the research on WAAM process control is relatively insufficient. The feedback signals in the AM process mainly include layer height, layer width, the temperature of the melt pool, and tool distance. The sensors used to measure feedback signals comprise of CCD camera, pyrometer, laser scanner, and so on. Many advanced control algorithms also have been applied in AM process control, such as predictive control, fuzzy control, and adaptive control.

5. Proposed framework

This study aims to provide readers with knowledge, strategy, and mothed for process monitoring and control in WAAM. Although there have been certain related research efforts in these fields, they are still separate. This study gathers and categorizes the previous study. As an emerging technology, the research on WAAM process monitoring is still limited. Therefore, this article also reviews research effort in laser AM and arc welding process, which has a similar process with WAAM. In order to make the reviewed content more specific and provide readers with inspiration, a framework was proposed out as an example in this section. This framework borrows ideas from previous research. At present, there is still no commercial WAAM automatic system available. This framework will help promote the development of WAAM in both academia and industry.

Based on the review, a process monitoring and control framework is proposed for GMAW based WAAM system. As shown in Fig. 12, the system consists of two subsystems: multiple-sensor monitoring module and control module. The monitoring system is responsible for capturing process signals and proving warning of defects. The function of the control system is to regulate the bead geometry and heat input.

The overall goal of this monitoring and control system is to improve the process stability, geometrical accuracy, production quality, and implement online diagnosis of defects for WAAM. Considering the feasibility for real-time monitoring in realistic production, sensing methods, with sensitive, reliable and stable properties, are more preferred to be utilized in our proposed framework. Methods like high-speed camera, X-ray and neutron diffraction, which are high-cost and more applicable in the laboratory, will not be included.

5.1. Multiple sensor monitoring system

Based on the literature review, a multiple sensor based monitoring system for WAAM process was proposed, which aim to detect different types of defects and process instability. The sensors Integrated includes CCD camera, 3D Scanner, Electrical Sensor, spectrometer and acoustic sensor. This multiple-sensor system will be able to monitor different object during WAAM process. The temperature of deposition surface will be monitored by pyrometer and thermal camera. The morphology of deposition surface will be measured by the laser scanner. In order to monitor melt pool, CCD camera will be utilized. Therefore, the surface morphology and temperature filed can be obtained. During WAAM process, electrical arc may contain abundant information, which is able to reflect welding quality. Therefore, the spectral signal of welding arc will be collected by a spectrometer, and the welding voltage and

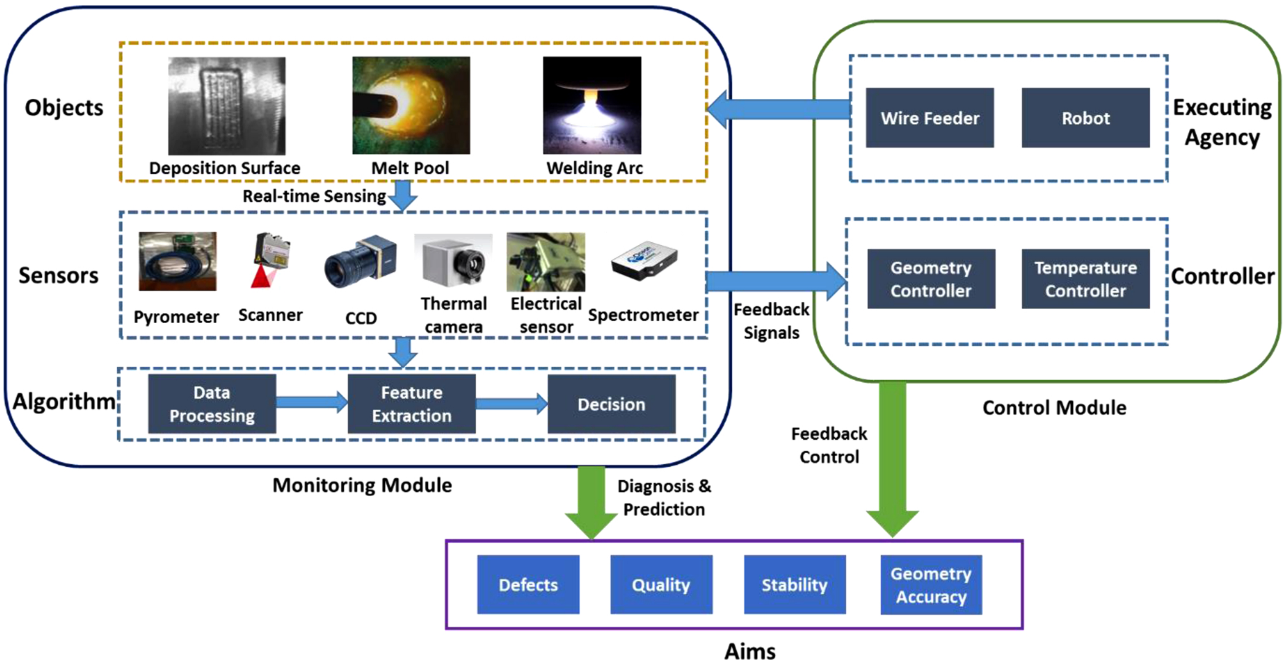

Fig. 12. Monitoring and control system of WAAM.

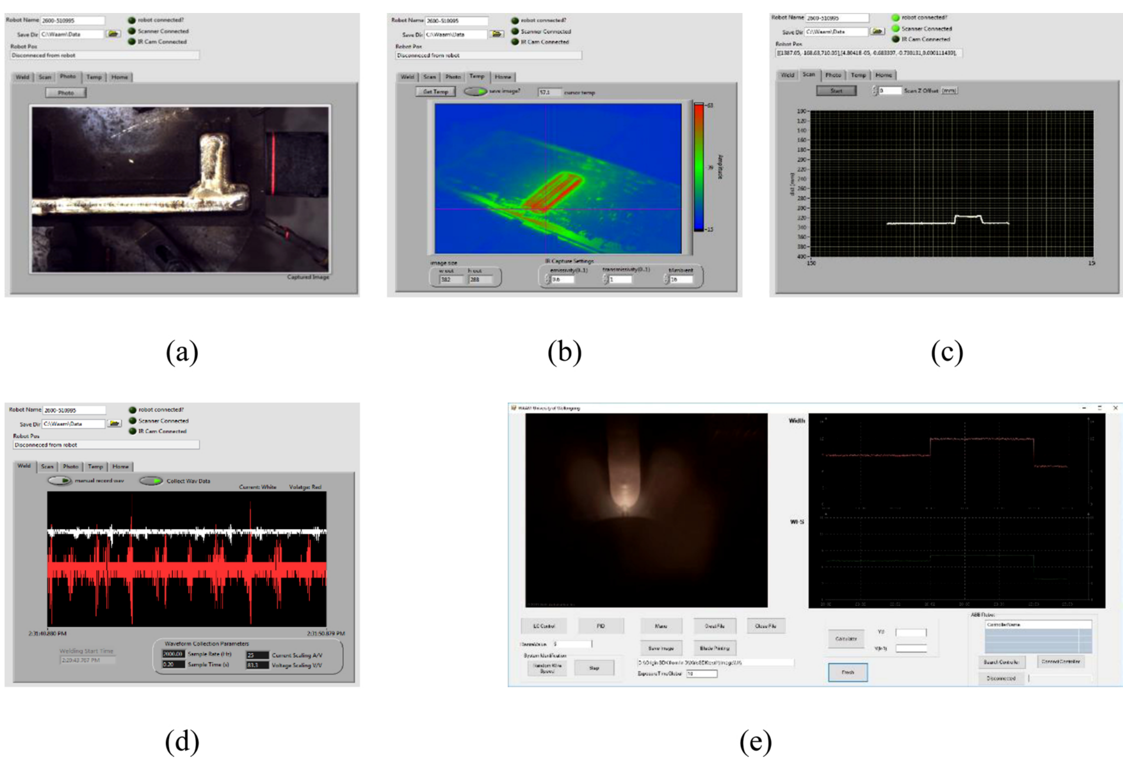

Fig. 13. Illustration of monitoring software interface of different sensors. (a) Camera (b) Thermal camera (c) Laser scanner (d) electrical sensors (e) Melt pool vision sensor.

current will be monitored by electrical sensors. Fig. 13 is an illustration of a part of software interfaces of monitoring system for various sensors.

However, the raw signals can't reflect the specific phenomenon directly, therefore data processing, feature extraction and decision making will be implemented in algorithm layer. For example, deep learning neural network could be used to extract features from melt pool image. Based on deep learning model, different welding states and some defects can be determined. In spectral signals and electrical signals, abnormality could be diagnosed by classification algorithms of machine learning, such as Support Vector Machine, K-Nearest Neighbor and Random Forest. The decision making module will implement the tasks like defects warning, parameter adjustment, process pause, and removal of defect part. For example, when the monitoring system discriminate the generation of porosity, which can't be accepted according to the quality requirement, then surface machining will be performed on this layer to remove the porosity. Besides, when the thermal sensors capture the temperature of bead surface, action judgement will be triggered. If the temperature beyond the pre-set value, then decision

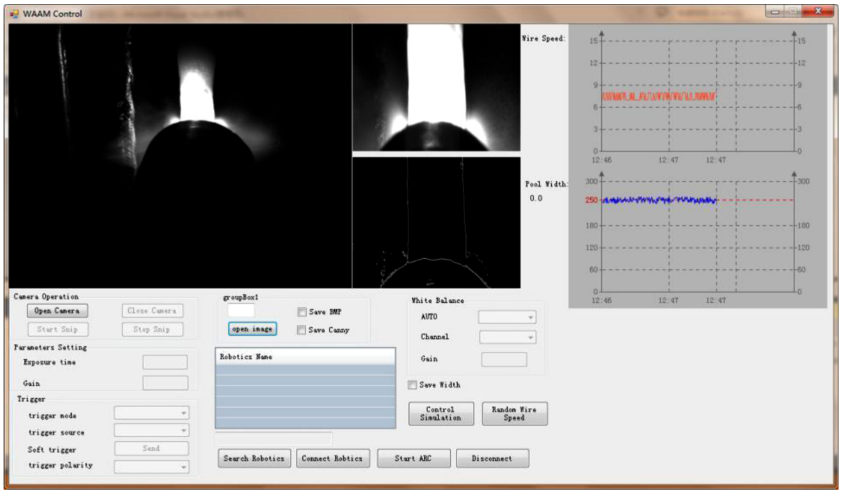

Fig. 14. Interface of control program.

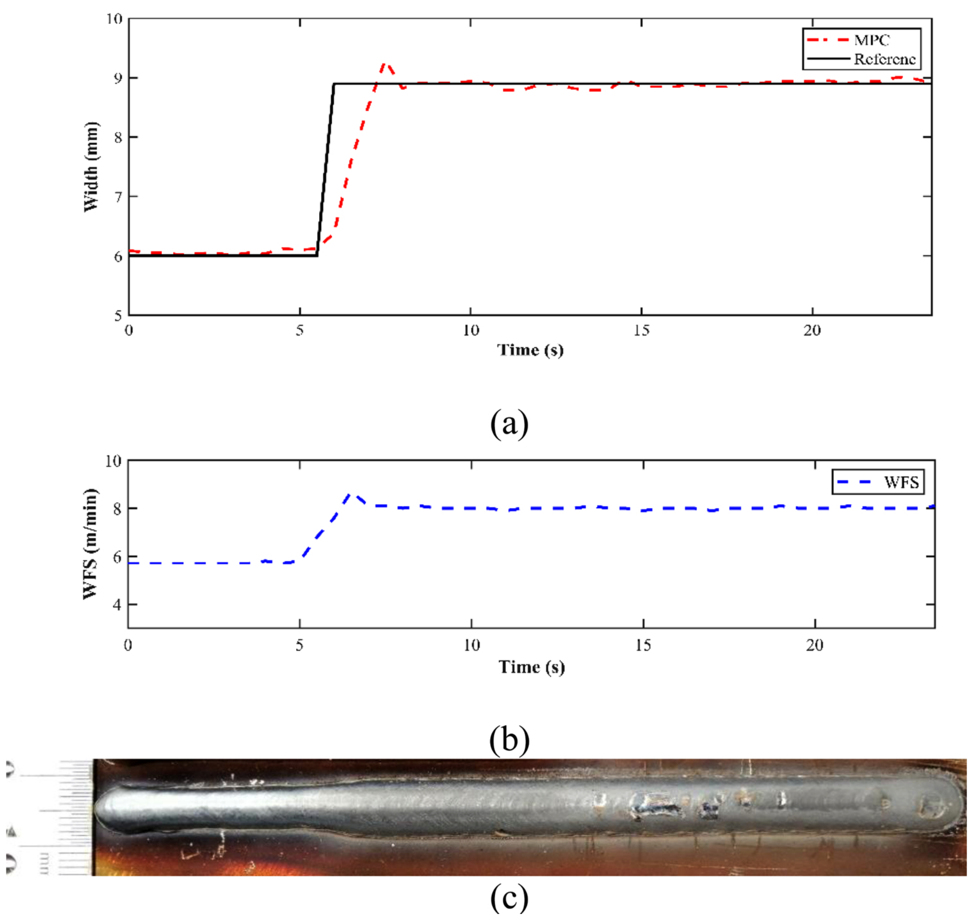

Fig. 15. Control performance of MPC.

module will pause the WAAM process and start cooling. When the bead surface temperature cooling to a certain value, the WAAM process will continue.

5.2. Control system

In order to achieve a good quality and process stability for WAAM, feedback controllers will be developed for the automatic WAAM system. Width and height are the most important geometry feature of deposition layer. Therefore, they will be regulated by advanced controllers. The interface of the bead with control program is shown in Fig. 14, which is developed by C#. This control program implements image processing, control algorithm and hardware communication. As illustrated in Fig. 15, it's a single bead deposited under the control of Model Predictive Control (MPC) algorithm. Fig. 15(a) presents the width of single bead under MPC control, and Fig. 15(b) presents the wire feed speed (WFS) calculated by MPC controller during control process. The initial reference point was set to be 6 mm and then increased to 9 mm. It can be seen that the MPC is capable to track varying set-value with little overshoot and acceptable responding time.

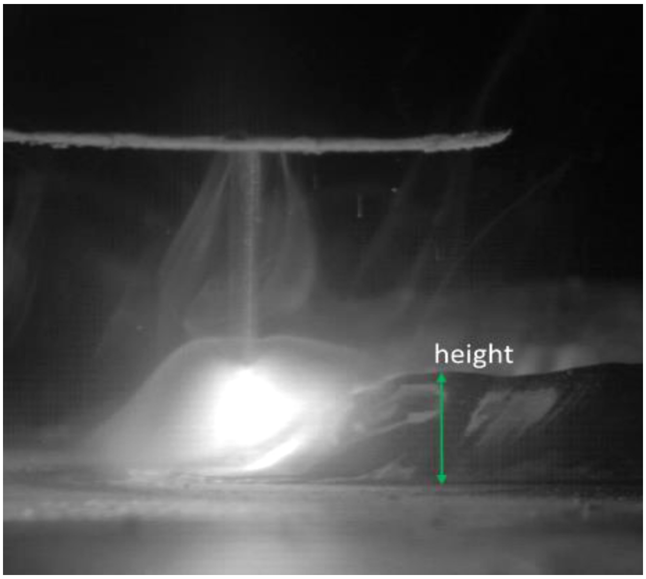

Fig. 16. welding image from side view.

Fig. 16 shows the image of welding area from a side view during WAAM process, which is captured by Xiris welding camera. It can be seen that the layer height could be measured on the image. Furthermore, feedback control for layer height will be implemented in the future.

6. Conclusion

The lack of robustness and repeatability of metal AM processes has been widely pointed out as one major issue that deserves considerable research efforts and technological advances. Therefore development and implementation of monitoring and control strategies possess a priority to push forward the industrial breakthrough of metal AM technology. In this paper, a comprehensive review of research efforts in area of process monitoring and control for AM was provided. Defects of AM, and its related signal and sensing method were categorized and discussed. Different control methods were reviewed and categorized according to its process type, control object and algorithm type. Furthermore, a framework of automatic WAAM system was proposed based on literature review. The proposed automatic WAAM system consists of two modules: multiple-sensor monitoring module and multiple-controller system. The proposed framework can help push forward the development of WAAM in both research and industry.

7. Future outlook

In the future, more artificial intelligence technology should be applied in WAAM. For instance, deep learning based pattern recognized technology could be utilized to achieve melting pool classification, surface defects inspection and other signals analysis. Reinforcement learning [119] could be utilized to realize robot path autonomous planning, parameter optimization and process control for WAAM. With the development Industry 4.0, the concept of Internet of Thing could help to realize the unmanned workshops for WAAM and the manpower can be saved efficiently. The concept of Big Data will help to realize the data sharing and processing, which could improve the CAD design, process optimization, and quality control for WAAM.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors gratefully acknowledge the China Scholarship Council for financial support (NO. 201704910782) and UOW Welding and Industrial Automation Research Centre .

References

[1] Abe T, Sasahara H. Dissimilar metal deposition with a stainless steel and nickel-based alloy using wire and arc-based additive manufacturing. Precis Eng 2016;45:387–95.
[2] Zhou X, et al. Three-dimensional numerical simulation of arc and metal transport in arc welding based additive manufacturing. Int J Heat Mass Transf 2016;103:521–37.
[3] Wang F, et al. Microstructure and mechanical properties of wire and arc additive manufactured Ti-6Al-4V. Metall Mater Trans A 2013;44(2):968–77.
[4] Ding D, et al. Automatic multi-direction slicing algorithms for wire based additive manufacturing. Robot Comput Integr Manuf 2016;37:139–50.
[5] Xiong J, et al. Vision-sensing and bead width control of a single-bead multi-layer part: material and energy savings in GMAW-based rapid manufacturing. J Clean Prod 2013;41:82–8.
[6] Colegrove PA, et al. High pressure interpass rolling of wire + arc additively manufactured titanium components. Advanced materials research. Trans Tech Publ.; 2014.
[7] Ralph, B., Method of making decorative articles. 1925, Google Patents.
[8] Busachi A, et al. Designing a WAAM based manufacturing system for defence applications. Procedia CIRP 2015;37:48–53.
[9] Gisario A, et al. Metal additive manufacturing in the commercial aviation industry: a review. J Manuf Syst 2019;53:124–49.
[10] Ding D, et al. Wire-feed additive manufacturing of metal components: technologies, developments and future interests. Int J Adv Manuf Technol 2015;81(1–4):465–81.
[11] Wu B, et al. A review of the wire arc additive manufacturing of metals: properties, defects and quality improvement. J Manuf Process 2018;35:127–39.
[12] Harris ID, Director A. Development and implementation of metals additive manufacturing. New Orleans: DOT International; 2011.
[13] Bourell DL, Leu MC, Rosen DW. Roadmap for additive manufacturing: identifying the future of freeform processing. Austin, TX: The University of Texas at Austin; 2009. p. 11–5.
[14] Wang B, et al. Intelligent welding system technologies: state-of-the-art review and perspectives. J Manuf Syst 2020;56:373–91.
[15] Denlinger ER, et al. Effect of inter-layer dwell time on distortion and residual stress in additive manufacturing of titanium and nickel alloys. J Mater Process Technol 2015;215:123–31.
[16] Zhu H, Lu L, Fuh J. Study on shrinkage behaviour of direct laser sintering metallic powder. Proc Inst Mech Eng Part B: J Eng Manuf 2006;220(2):183–90.
[17] Wenbin H, Yong Tsui L, Haiqing G. A study of the staircase effect induced by material shrinkage in rapid prototyping. Rapid Prototyp J 2005;11(2):82–9.
[18] Ding D, et al. Towards an automated robotic arc-welding-based additive manufacturing system from CAD to finished part. Comput Des 2016;73:66–75.
[19] Xiong J, et al. Bead geometry prediction for robotic GMAW-based rapid manufacturing through a neural network and a second-order regression analysis. J Intell Manuf 2014;25(1):157–63.
[20] Nagesh D, Datta G. Genetic algorithm for optimization of welding variables for height to width ratio and application of ANN for prediction of bead geometry for TIG welding process. Appl Soft Comput 2010;10(3):897–907.
[21] Haleem A, Javaid M. Additive manufacturing applications in industry 4.0: a review. J Ind Integr Manag 2019;4(04):1930001.
[22] Dilberoglu UM, et al. The role of additive manufacturing in the era of industry 4.0. Procedia Manuf 2017;11:545–54.
[23] Wang Y, et al. Weld reinforcement analysis based on long-term prediction of molten pool image in additive manufacturing. IEEE Access 2020;8:69908–18.
[24] Nguyen L, Buhl J, Bambach M. Continuous Eulerian tool path strategies for wire-arc additive manufacturing of rib-web structures with machine-learning-based adaptive void filling. Addit Manuf 2020:101265.
[25] Deng J, et al. Bead geometry prediction for multi-layer and multi-bead wire and arc additive manufacturing based on XGBoost. Transactions on intelligent welding manufacturing. Springer; 2019. p. 125–35.
[26] Tang S, et al. An online surface defects detection system for AWAM based on deep learning. Solid Freeform Fabrication 2017: Proc. of the 28th Annual International Solid Freeform Fabrication Symposium–An Additive Manufacturing Conference 2017.
[27] Sreedhar U, et al. Automatic defect identification using thermal image analysis for online weld quality monitoring. J Mater Process Technol 2012;212(7):1557–66.
[28] Huang N, et al. Interval model control of human welder's movement in machine-assisted manual GTAW torch operation. Int J Adv Manuf Technol 2015;86(1–4):397–405.
[29] Huang Y, et al. EMD-based pulsed TIG welding process porosity defect detection and defect diagnosis using GA-SVM. J Mater Process Technol 2017;239:92–102.
[30] Yu H, et al. On-line monitor of hydrogen porosity based on arc spectral information in Al–Mg alloy pulsed gas tungsten arc welding. Opt Laser Technol

2015;70:30–8.
[31] Yusof MFM, et al. Porosity detection by analyzing arc sound signal acquired during the welding process of gas pipeline steel. Int J Adv Manuf Technol 2016;89(9–12):3661–70.
[32] Slotwinski JA, Garboczi EJ. Porosity of additive manufacturing parts for process monitoring. AIP Conference Proceedings. 2014.
[33] Rieder H, et al. Online monitoring of additive manufacturing processes using ultrasound. 11th European Conference on Non-Destructive Testing (ECNDT). 2014.
[34] Wei E, et al. Detection of weld surface porosity by statistical analysis of arc current in gas metal arc welding. J Manuf Process 2001;3(1):50–9.
[35] Thekkuden DT, et al. Instant detection of porosity in gas metal arc welding by using probability density distribution and control chart. Int J Adv Manuf Technol 2018;95(9–12):4583–606.
[36] Sumesh A, et al. Decision tree based weld defect classification using current and voltage signatures in GMAW process. Mater Today Proc 2018;5(2):8354–63.
[37] Mireles J, et al. Analysis and correction of defects within parts fabricated using powder bed fusion technology. Surf Topogr Metrol Prop 2015;3(3):034002.
[38] Boateng FT, et al. Real-time radiography for observation of crack growth during GTA welding. Weld World 2016;60(5):931–7.
[39] Broberg P. Surface crack detection in welds using thermography. NDT E Int 2013;57:69–73.
[40] García de la Yedra A, et al. Online cracking detection by means of optical techniques in laser-cladding process. Struct Control Health Monit 2019;26(3):e2291.
[41] Droubi MG, et al. Acoustic emission method for defect detection and identification in carbon steel welded joints. J Constr Steel Res 2017;134:28–37.
[42] Strantza M, et al. Acoustic emission monitoring of crack propagation in additively manufactured and conventional titanium components. Mech Res Commun 2017;84:8–13.
[43] Karlsson L. Crack Detection in welding process using acoustic emission. 2010.
[44] Zhang Y, et al. Neural network monitoring of aluminum alloy spot welding crack based on acoustic emission signal. J Mech Eng 2016;52(16):1–7.
[45] Yusa N, et al. Detection of embedded fatigue cracks in Inconel weld overlay and the evaluation of the minimum thickness of the weld overlay using eddy current testing. Nucl Eng Des 2006;236(18):1852–9.
[46] Khanzadeh M, et al. In-situ monitoring of melt pool images for porosity prediction in directed energy deposition processes. IISE Trans 2018;51(5):437–55.
[47] Zhang Z, et al. Real-time defect detection in pulsed GTAW of Al alloys through online spectroscopy. J Mater Process Technol 2013;213(7):1146–56.
[48] Mirapeix J, et al. Real-time arc-welding defect detection and classification with principal component analysis and artificial neural networks. NDT E Int 2007;40(4):315–23.
[49] Mirapeix J, et al. Real-time arc welding defect detection technique by means of plasma spectrum optical analysis. NDT E Int 2006;39(5):356–60.
[50] Zhang Z, et al. Online welding quality monitoring based on feature extraction of arc voltage signal. Int J Adv Manuf Technol 2014;70(9–12):1661–71.
[51] Hu D, Kovacevic R. Modelling and measuring the thermal behaviour of the molten pool in closed-loop controlled laser-based additive manufacturing. Proc Inst Mech Eng Part B: J Eng Manuf 2003;217(4):441–52.
[52] Han L, Liou FW, Musti S. Thermal behavior and geometry model of melt pool in laser material process. J Heat Transfer 2005;127(9):1005–14.
[53] Aendenroomer A, Den Ouden G. Weld pool oscillation as a tool for penetration sensing during pulsed GTA welding. Weld J-N Y 1998;77. p. 181-s.
[54] Carlson N, Johnson J. Ultrasonic sensing of weld pool penetration. Weld J (Miami) (USA) 1988;67(11).
[55] Pal K, Pal SK. Monitoring of weld penetration using arc acoustics. Mater Manuf Process 2011;26(5):684–93.
[56] Yoo CD, Richardson RW. An experimental study on sensitvity and signal characteristics of welds pool oscillation. Trans Jpn Weld Soc 1993;24(2):54–62.
[57] Xiao Y, Den Ouden G. Weld pool oscillation during GTA welding of mild steel. Weld J-N Y 1993;72. p. 428-s.
[58] Criales LE, et al. Laser powder bed fusion of nickel alloy 625: experimental investigations of effects of process parameters on melt pool size and shape with spatter analysis. Int J Mach Tools Manuf 2017;121:22–36.
[59] Bicknell A, Smith J, Lucas J. Infrared sensor for top face monitoring of weld pools. Meas Sci Technol 1994;5(4):371.
[60] Davis TA, Shin YC. Vision-based clad height measurement. Mach Vis Appl 2010;22(1):129–36.
[61] Pan Z, et al. Arc welding processes for additive manufacturing: a review. Transactions on intelligent welding manufacturing. Springer; 2018. p. 3–24.
[62] Clijsters S, et al. In situ quality control of the selective laser melting process using a high-speed, real-time melt pool monitoring system. Int J Adv Manuf Technol 2014;75(5–8):1089–101.
[63] Repossini G, et al. On the use of spatter signature for in-situ monitoring of laser powder bed fusion. Addit Manuf 2017;16:35–48.
[64] Grasso M, et al. In situ monitoring of selective laser melting of zinc powder via infrared imaging of the process plume. Robot Comput Integr Manuf 2018;49:229–39.
[65] Zhang Y, et al. Extraction and evaluation of melt pool, plume and spatter information for powder-bed fusion AM process monitoring. Mater Des 2018;156:458–69.
[66] Gobert C, et al. Application of supervised machine learning for defect detection during metallic powder bed fusion additive manufacturing using high resolution imaging. Addit Manuf 2018;21:517–28.
[67] Zhan Q, et al. A wire deflection detection method based on image processing in wire + arc additive manufacturing. Int J Adv Manuf Technol 2016;89(1–4):755–63.
[68] Bonaccorso F, Cantelli L, Muscato G. An arc welding robot control for a shaped metal deposition plant: modular software interface and sensors. IEEE Trans Ind Electron 2011;58(8):3126–32.
[69] Beyer E, et al. Identification of phase transformation using optical emission spectroscopy for direct metal deposition process. 2012. p. 82390G. 8239.
[70] Song L, et al. Real-time composition monitoring using support vector regression of laser-induced plasma for laser additive manufacturing. IEEE Trans Ind Electron 2017;64(1):633–42.
[71] Ya W, et al. Spectroscopic monitoring of metallic bonding in laser metal deposition. J Mater Process Technol 2015;220:276–84.
[72] Gaja H, Liou F. Defects monitoring of laser metal deposition using acoustic emission sensor. Int J Adv Manuf Technol 2016;90(1–4):561–74.
[73] Shevchik SA, et al. Acoustic emission for in situ quality monitoring in additive manufacturing using spectral convolutional neural networks. Addit Manuf 2018;21:598–604.
[74] Ye D, et al. Defect detection in selective laser melting technology by acoustic signals with deep belief networks. Int J Adv Manuf Technol 2018;96(5–8):2791–801.
[75] Wang F, et al. Online study of cracks during laser cladding process based on acoustic emission technique and finite element analysis. Appl Surf Sci 2008;255(5):3267–75.
[76] Pal K, Bhattacharya S, Pal SK. Investigation on arc sound and metal transfer modes for on-line monitoring in pulsed gas metal arc welding. J Mater Process Technol 2010;210(10):1397–410.
[77] Pal K, Bhattacharya S, Pal SK. Prediction of metal deposition from arc sound and weld temperature signatures in pulsed MIG welding. Int J Adv Manuf Technol 2009;45(11–12):1113–30.
[78] Bhattacharya S, Pal K, Pal SK. Multi-sensor based prediction of metal deposition in pulsed gas metal arc welding using various soft computing models. Appl Soft Comput 2012;12(1):498–505.
[79] Saad E, Wang H, Kovacevic R. Classification of molten pool modes in variable polarity plasma arc welding based on acoustic signature. J Mater Process Technol 2006;174(1–3):127–36.
[80] Chen B, Chen S. A study on applications of multi-sensor information fusion in pulsed-GTAW. Robotic welding, intelligence and automation. Springer; 2011. p. 245–52.
[81] Van Bohemen S, Hermans M, Den Ouden G. Monitoring of martensite formation during welding by means of acoustic emission. J Phys D: Appl Phys 2001;34(22):3312.
[82] Sumesh A, et al. Use of machine learning algorithms for weld quality monitoring using acoustic signature. Procedia Comput Sci 2015;50:316–22.
[83] Krauss H, Eschey C, Zaeh M. Thermography for monitoring the selective laser melting process. Proceedings of the Solid Freeform Fabrication Symposium 2012.
[84] Khanzadeh M, et al. A methodology for predicting porosity from thermal imaging of melt pools in additive manufacturing thin wall sections. ASME 2017 12th International Manufacturing Science and Engineering Conference Collocated With the JSME/ASME 2017 6th International Conference on Materials and Processing. 2017.
[85] Mani M, et al. Measurement science needs for real-time control of additive manufacturing powder bed fusion processes. 2015.
[86] Xiong J, Zhang G. Adaptive control of deposited height in GMAW-based layer additive manufacturing. J Mater Process Technol 2014;214(4):962–8.
[87] Doumanidis C, Kwak Y-M. Geometry modeling and control by infrared and laser sensing in thermal manufacturing with material deposition. J Manuf Sci Eng 2001;123(1):45–52.
[88] Doumanidis C, Kwak Y-M. Multivariable adaptive control of the bead profile geometry in gas metal arc welding with thermal scanning. Int J Press Vessel Pip 2002;79(4):251–62.
[89] Xiong J, Yin Z, Zhang W. Closed-loop control of variable layer width for thin-walled parts in wire and arc additive manufacturing. J Mater Process Technol 2016;233:100–6.
[90] Heralić A, Christiansson A-K, Lennartson B. Height control of laser metal-wire deposition based on iterative learning control and 3D scanning. Opt Lasers Eng 2012;50(9):1230–41.
[91] Heralić A, et al. Increased stability in laser metal wire deposition through feedback from optical measurements. Opt Lasers Eng 2010;48(4):478–85.
[92] Farshidianfar MH, et al. System identification and height control of laser cladding using adaptive neuro-fuzzy inference systems. International Congress on Applications of Lasers & Electro-Optics. 2013.
[93] Zeinali M, Khajepour A. Height control in laser cladding using adaptive sliding mode technique: theory and experiment. J Manuf Sci Eng 2010;132(4):041016.
[94] Devesse W, et al. Hardware-in-the-loop control of additive manufacturing processes using temperature feedback. J Laser Appl 2016;28(2):022302.
[95] Hua Y, Choi J. Adaptive direct metal/material deposition process using a fuzzy logic-based controller. J Laser Appl 2005;17(4):200–10.
[96] Song L, et al. Control of melt pool temperature and deposition height during direct metal deposition process. Int J Adv Manuf Technol 2011;58(1–4):247–56.
[97] Hofman JT, et al. A camera based feedback control strategy for the laser cladding process. J Mater Process Technol 2012;212(11):2455–62.
[98] Salehi D, Brandt M. Melt pool temperature control using LabVIEW in Nd:YAG laser blown powder cladding process. Int J Adv Manuf Technol 2005;29(3–4):273–8.
[99] Chen H-Y, Huang S-J. Adaptive fuzzy sliding-mode control for the Ti6Al4V laser alloying process. Int J Adv Manuf Technol 2004;24(9–10):667–74.
[100] Hagqvist P, et al. Resistance based iterative learning control of additive manufacturing with wire. Mechatronics 2015;31:116–23.
[101] Zeinali M, Khajepour A. Development of an adaptive fuzzy logic-based inverse

dynamic model for laser cladding process. Eng Appl Artif Intell 2010;23(8):1408–19.
[102] Han W, Jafari MA. Coordination control of positioning and deposition in layered manufacturing. IEEE Trans Ind Electron 2007;54(1):651–9.
[103] Hu D, Kovacevic R. Sensing, modeling and control for laser-based additive manufacturing. Int J Mach Tools Manuf 2003;43(1):51–60.
[104] Cao X, Ayalew B. Robust multivariable predictive control for laser-aided powder deposition processes. J Franklin Inst 2019;356(5):2505–29.
[105] Wang D, Chen X. A multirate fractional-order repetitive control for laser-based additive manufacturing. Control Eng Pract 2018;77:41–51.
[106] Renken V, et al. Development of an adaptive, self-learning control concept for an additive manufacturing process. Cirp J Manuf Sci Technol 2017;19:57–61.
[107] Tang L, Landers RG. Melt pool temperature control for laser metal deposition processes—part II: layer-to-layer temperature control. J Manuf Sci Eng 2010;132(1):011011.
[108] Sammons PM, Bristow DA, Landers RG. Iterative learning control of bead morphology in laser metal deposition processes. 2013 American Control Conference. 2013.
[109] Tang L, Landers RG. Melt pool temperature control for laser metal deposition processes—part I: online temperature control. J Manuf Sci Eng 2010;132(1):011010.
[110] Devesse W, De Baere D, Guillaume P. Design of a model-based controller with temperature feedback for laser cladding. Phys Procedia 2014;56:211–9.
[111] Bi G, et al. Characterization of the process control for the direct laser metallic powder deposition. Surf Coat Technol 2006;201(6):2676–83.
[112] Farshidianfar MH, Khajepour A, Gerlich A. Real-time control of microstructure in laser additive manufacturing. Int J Adv Manuf Technol 2015;82(5–8):1173–86.
[113] Li F, et al. Adaptive process control of wire and arc additive manufacturing for fabricating complex-shaped components. Int J Adv Manuf Technol 2018;96:871–9.
[114] Kwak Y-M, Doumanidis CC. Geometry regulation of material deposition in near-net shape manufacturing by thermally scanned welding. J Manuf Process 2002;4(1):28–41.
[115] Smith JS, Nobertro Pires J, Balfour C. Real-time top-face vision based control of weld pool size. Ind Robot Int J 2005;32(4):334–40.
[116] Fan H, et al. Low-cost infrared sensing system for monitoring the welding process in the presence of plate inclination angle. J Mater Process Technol 2003;140(1–3):668–75.
[117] Liu YK, Zhang YM. Model-based predictive control of weld penetration in gas tungsten arc welding. IEEE Trans Control Syst Technol 2013;22(3):955–66.
[118] Liu Y, Zhang Y. Control of 3D weld pool surface. Control Eng Pract 2013;21(11):1469–80.
[119] Kaelbling LP, Littman ML, Moore AW. Reinforcement learning: a survey. J Artif Intell Res 1996;4:237–85.