Progress and perspectives of in-situ optical monitoring in laser beam welding: sensing, characterization and modeling

Di Wu[a,b,d*], Peilei Zhang[a,b,e], Zhishui Yu[a,b], Yanfeng Gao[a,c], Hua Zhang[a,c], Huabin Chen[d,*], Shanben Chen[d], YingTao Tian[f]

[a] *School of Materials Engineering, Shanghai University of Engineering Science, Shanghai 201620, China*
[b] *Shanghai Collaborative Innovation Center of Laser of Manufacturing Technology, Shanghai 201620, China*
[c] *Shanghai Collaborative Innovation Center of Intelligent Manufacturing Robot Technology for Large Components, Shanghai 201620, China*
[d] *Shanghai Jiao Tong University, Shanghai 200240, China*
[e] *Fraunhofer Institute for Laser Technology ILT, Aachen 52074, Germany*
[f] *Department of Engineering, Lancaster University, Lancaster LA1 4YW, United Kingdom*

Abstract:

Laser beam welding manufacturing (LBW), being a promising joining technology with superior capabilities of high-precision, good-flexibility and deep penetration, has attracted considerable attention over the academic and industry circles. To date, the lack of repeatability and stability are still regarded as the critical technological barrier that hinders its broader applications especially for high-value products with demanding requirements. One significant approach to overcome this formidable challenge is in-situ monitoring combined with artificial intelligence (AI) techniques, which has been explored by great research efforts. The main goal of monitoring is to gather essential information on the process and to improve the understanding of the occurring complicated weld phenomena. This review firstly describes ongoing work on the in-situ optical sensing, behavior characterization and process modeling during dynamic LBW process. Then, much emphasis has been placed on the optical radiation techniques, such as multi-spectral photodiode, spectrometer, pyrometer and high-speed camera for observing the laser physical phenomenon including melt pool, keyhole and vapor plume. In particular, the advanced image/signal processing techniques and machine-learning models are addressed, in order to identify the correlations between process parameters, process signatures and product qualities. Finally, the major challenges and potential solutions are discussed to provide an insight on what still needs to be achieved in the field of process monitoring for metal-based LBW processes. This comprehensive review is intended to provide a reference of the state-of-the-art for those seeking to introduce intelligent welding capabilities as they improve and control the welding quality.

Keywords: Laser beam welding; Optical monitoring; Behavior characterization; Machine learning; Weld quality; Process model

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* Corresponding author:

Email address: wudi@sues.edu.cn (Di Wu), hbchen@sjtu.edu.cn (Huabin Chen)

1. Introduction

Compared with traditional arc welding techniques, laser beam welding (LBW) shows significant superiority in realizing automatic manufacturing processing, high-efficiency production and accessing high-quality weld joints [1]. Also, LBW has gained great popularity as a promising joining technology with deep penetration depth, high precision, less distortion and good flexibility [2]. As an advanced manufacturing technique, LBW has been widely applied to various industry fields, ranging from small-scale manual welding to fully-automatic welding in the automotive, aerospace, shipbuilding and electronic manufacturing fields[3]. However, LBW involves a lot of complicated physical processes including metal melting/solidification, keyhole formation and laser-metal interaction, which results in very complex transport phenomena, thus the resultant weld quality is easily affected by some process variables and defects including high-level of porosity [4], instabilities [5] and metal spatters [6]. The potential weld defects significantly weaken the mechanical properties of the welded parts and increased the risks of part fatigue, which resulting in a non-acceptable welding product.

In order to improve the product quality and restrain the weld defects, and further to better understand the in-process complex phenomena occurring in welding process, a series of in-situ monitoring approaches have been proposed to provide valuable information to characterize the process and control quality. The design idea of mainstream monitoring solutions mainly depend on the utilization of the consequent laser physical phenomena including melt pool, keyhole and plume within laser-metal interactions. These physical phenomena carries various types of welding information e.g. acoustic-emission [7]-[9], electrical [10]-[11], thermal radiation [12]-[13] and visual signals [14]-[16], which are closely linked to the welding process and joint quality. Therefore, the proper utilization of various monitoring sensors and systems is a crucial issue for exactly describing the laser welding process. For example, a microphone or piezoelectric element are used to collect the airborne and structure acoustic-emission (AE) signals. Vision sensors including charge-coupled device (CCD), complementary metal-oxide semiconductor (CMOS) and high-speed camera with special filters are applied to capture the images of the molten pool, plume and spatters. Spectrometer and photodiode-based sensors are utilized to collect the optical signals include visible light (VIS), infrared light (IR) and ultraviolet light (UV) wavelengths. The near-infrared (NIR) camera and pyrometer can be exploited to gather the thermal signals emitting from the welding zone [22]. Complex monitoring system usually consists of the above-mentioned sensors and various types of welding information will be more comprehensively collected.

In recent years, some published reviews [17]-[20] introduced the effective applications of various advanced sensing technology (i.e., vision camera, acoustic emissions, ultrasonic testing and eddy current technique) to laser welding detection and summarized the attempts to use artificial-intelligence (AI) technology for welding quality recognition. In addition, the University of Kentucky Welding Research Laboratory [21] systematically analyzed the advanced welding manufacturing as a three-step approaches: i) pre-design that selects process and joint design based on available processes; ii) design that uses models to predict the results from a given set of welding parameters; and iii) real-time sensing and control that overcome the deviations of welding conditions by adjusting the parameters based on in-situ monitoring and adaptive control. As a matter of fact, most of the mentioned studies mainly demonstrated the capability of measuring relevant signatures and investigated the influences of the welding parameters on those measured quantities. Moreover, it is predominantly the optical sensing techniques have been selected for in-situ, real-time monitoring the LBW process due to a series of advantages of non-contact, intuitive, integrated, flexible and multifunctional [22]. Indeed, in the mainstream literature, the key term "monitoring" is applied to indicate the in-situ data gathering, feature extraction and dynamic process modeling. From a statistical perspective, the term "monitoring" refers not only to the data gathering but also to the process/defects identification through automated alarm rules [23]. This kind of monitoring methodology is needed to actually improve the intelligent capabilities of next-generation LBW system. Therefore, the scope of this review mainly focuses on the optical in-process monitoring with respect to observing, experimenting and systematic gathering of information, special attention is given to discussions on: in-situ sensing technology, multi-feature characterization and process modeling.

Fig. 1 shows the content structure of this review, which consists of two mainstream processes. In forward-process (Sec. 2-Sec. 4), it begins with a detailed introduction about the basics of laser welding and monitoring methodology, and provided the common and advanced optical sensing techniques for observing the laser physical phenomenon in Sec 3. Then, to achieve a quantitative characterization of welding process, the optical feature extraction based on imaging/signal processing methods were presented respectively in Sec 4. In feedback-process from Sec. 5, the data-driven modeling based on machine learning techniques were summarized for predicting and controlling the weld quality. Finally, Sec. 6 depicts the potential and challenges about the intelligent monitoring of laser welding process and Sec. 7 concludes this review.

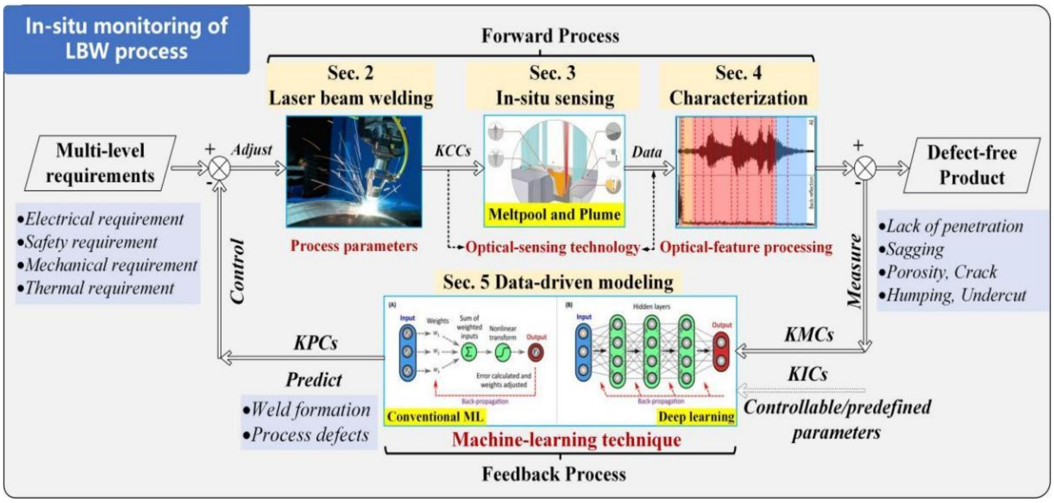

Fig. 1. The flow chart of in-situ monitoring process for advanced laser beam welding manufacturing in this review.

2. Fundamentals of LBW and process monitoring

2.1 Physical characteristics of LBW process

Contrary to arc welding processes, the laser-based manufacturing technique greatly enhances the processing flexibility with the contactless nature of laser light. As a high-power-density heat source, the laser beam quickly heats up the metallic plate surface to a certain temperature, at which the hot melt metal starts to vaporize at the position of laser beam focus [1]. As shown in Fig. 2, two different operational regimes of LBW process including heat-conduction type and keyhole type exist governed by the laser power density [24]. During the conduction welding process, the focused laser beam spot heats up the material to its melting temperature and then quickly creates a stable melt pool on the surface of metal, but the laser power density is not large enough to create boiling metal pool (see Fig. 2a). When the power density increases to evaporate the material, the laser beam then drills a deep and narrow capillary (keyhole) inside the melt pool. The keyhole will remain open and stable as the laser welding process takes place due to the increasing evaporation recoil pressure. In a stable keyhole, almost all the laser energy in the beam will be absorbed due to the beam entering into the hole and reflecting inside it before it is able to escape, as shown in Fig. 2b. Since the laser absorption is extremely high due to multi-reflection inwards in the case of a keyhole formation, a keyhole type-based deep penetration welding is regarded as an efficient joining process.

During laser welding process, a laser-induced plume (i.e., metallic vapour and plasma) comprising a bright plume of evaporated metallic atoms and vapors is ejected from laser-irradiated zone (especially a keyhole). The plume has a negative effect on the laser welding process. It ejects at high speeds of 20-250m/s from the keyhole opening and strongly depends on laser power applied [25]. At high laser beam powers, the attenuation occurs due to scattering and absorption of incident laser beam, which called the plasma-blocking effect. This leads to a lower penetration depth and process instabilities. Meantime, the spattering of melt droplets caused by a strong stream of the ejected plume, sometimes occurs from the inlet of a keyhole [26].

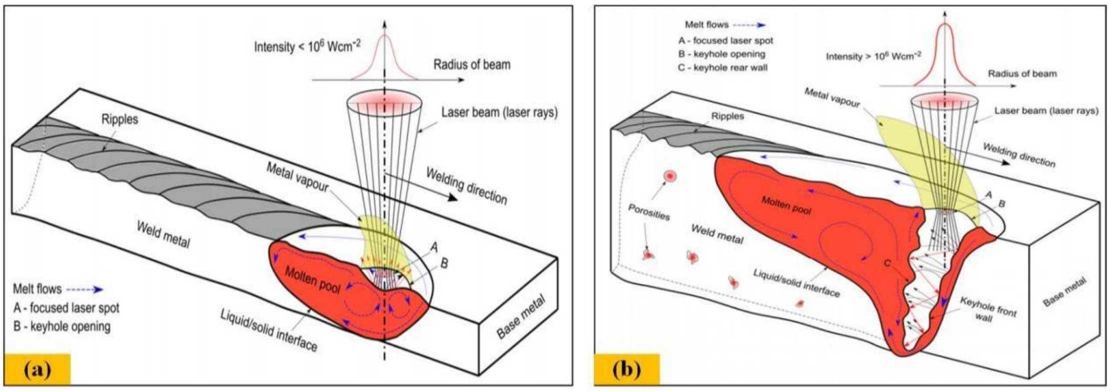

Fig. 2 Schematic drawing of laser beam physics in laser beam welding in case of (a) conduction welding and (b) keyhole welding modes [24].

2.2 Categories of laser welding defects

During LBW process, the weld characteristics including weld appearance and defects play an important role in deciding the mechanical properties, creep properties and weld quality [27]. In general, the weld appearance including penetration depth and bead width are the external manifestation of quality. The instability and regular collapse of keyhole can result in a series of weld defects including porosity, spatter or humping in deep penetration laser welding, which leading to a fracture or a disaster of manufactured goods under improper conditions [28].

Prior to further investigation into the in-process monitoring approach, a description of the weld defects is cited below aiming to provide a view as to the way the process parameters affect the formation of weld defects and what kinds of physical phenomena need to be monitored for the defect detection. Understanding the causes that lead to the creation of abnormalities and examining the relationship of sensing data with the creation of weld defects are paramount to achieving a high-quality weld product. The laser welding defects are often classified into two characteristic groups: i) geometrical/appearance defects and ii) internal/invisible defects, as shown in Fig. 3. Some important welding defects and their physical origin are summarized in Table. 1. From the above, it can be concluded that the formation of common defects in a weld is strongly related to the stability of keyhole, melt pool and plume. Therefore, it is vital of importance to monitor the occurring process phenomenon in order to prevent the weld defects, further to achieve the real-time controlling of the weld quality.

Table 1 Classification of laser welding defects and explanation of their physical causes.

Category	Defect Type	Explanation	Physical causes
Geometrical/ appearance defects	Burn-through	Melt in a molten pool drops down to form an underfilled bead	Too high heat input, excessively severe melt flow, unstable keyhole
	Undercut	A groove along the toe of the weld bead	Metal spattering from the internal keyhole
	Underfill	A concave surface of a weld bead	Backward flow of the melt pool around the blind keyhole
	Humping	The pushed molten metal from the rear keyhole wall towards the back	Narrow and long molten pool, collision of fluid flow
Internal/ invisible defects	Porosity	Blowhole, pore, wormhole or bubble inside the workpiece	The instability of the keyhole and melt pool
	Incomplete-penetration	Joint not completely penetrated	Low heat input and not fully-penetrated keyhole
	Cracking	Solidification crack was often found in the vicinity of vulnerable zone	Rapid cooling rate and large temperature gradient ofmelt pool

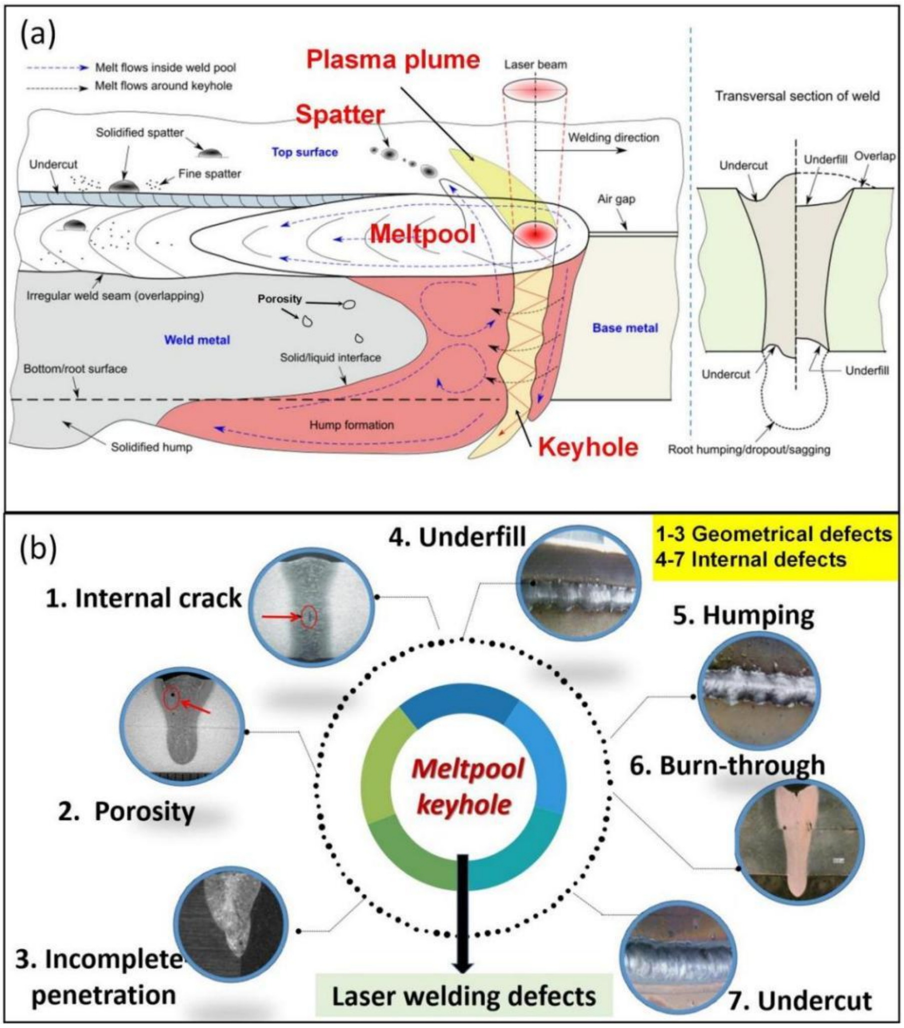

Fig. 3. Schematic illustration (a) of laser beam keyhole welding during full-penetration [24] and (b) examples of common welding defects.

2.3 Basics and challenges of in-situ monitoring

To obtain a solid understanding of the formation mechanisms of laser welding process and related defects, it is crucial to explore the causal relationships between the process parameters, process signatures and welding qualities, as depicted in Fig. 4. The process parameters referring to key input characteristics (*KICs*) are the “model inputs” and primarily determine the laser energy delivered to the surface of the worrkpiece and how that laser energy interacts with metallic materials. The process parameters can be categorized into either controllable variables (laser power, scan speed and defocusing, etc.) or predefined variables (material properties, laser types and workpiece conditions, etc.). The process signatures referring to key measurement characteristics (*KMCs*) are dynamic characteristics of the workpiece heating, melting and solidification processes as they occur during the laser welding. These signatures are often the morphology of melt pool/plume and optical radiation intensity, which depending on the physical phenomenon emitted from laser-metal interaction. In addition, the process qualities defining as key performance characteristics (*KPCs*), mainly includes the welding defects, penetration depth/status and bead widths, which directly determine the resultant weld quality.

Due to the high-dynamic and complex characteristics of laser-metal interaction, there exists some significant challenges in the process monitoring: 1) how to achieve the high-quality and fast-speed gathering of various optical signals under the lower SNR (signal-noise ratio) and strong metallic vapor/spatter circumstances; 2) how to reveal the internal relationship between the large amounts of optical information with random fluctuation (especially the radiation signals) and welding process/stability; 3) how to accurately predict/identify the final welding qualities (*KPCs*) under a time-varying and non-linearity process with many interacting factors (*KICs*).

To identify and overcome these critical challenges above, this paper presents a detailed review to introduce various monitoring methods in literature to make fundamental progress. It mainly consists of three successive steps: i) in-situ optical sensing that gather multi-dimensionality, multi-type and multi-scale data deriving from laser radiation; ii) quantitative behavior characterization that analyze and extract the optical signatures from the raw data for representing the physical phenomenon (melt pool, plume and spatters), iii) process modeling that apply machine learning algorithms to comprehensively identify the parameter-signature-quality relationship, further to facilitate the development of the in-process monitoring and develop towards real-time process control. The following sections will comprehensively review the recent research and development of each of these steps.

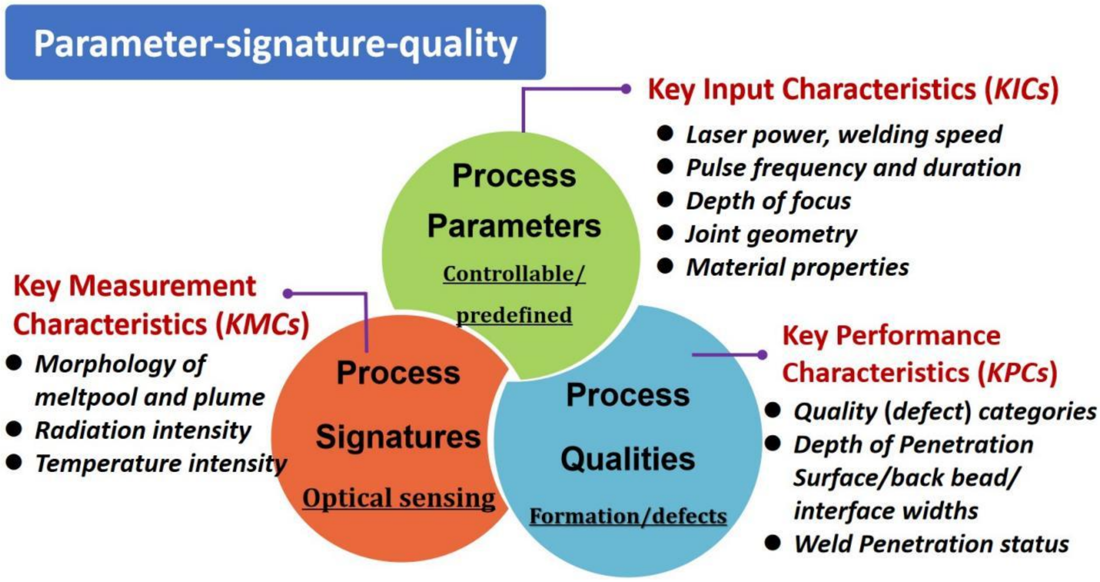

Fig. 4 Interrelation between process parameters, process signatures and process qualities.

3. Optical in-situ sensing technology

In Sec. 3, we reviews previous research efforts on multi-wave optical radiation sensing techniques for observing the melt pool and plume characteristics. The detailed classification of optical monitoring techniques are displayed in Fig.5, and the advantages and limitations of different techniques are summarized in Table 2. Except for conventional optical monitoring methods, some novel optical sensing methods including X-ray imaging and optical coherence imaging are depicted to directly observe the internal physical characteristics (keyhole depth and porosity).

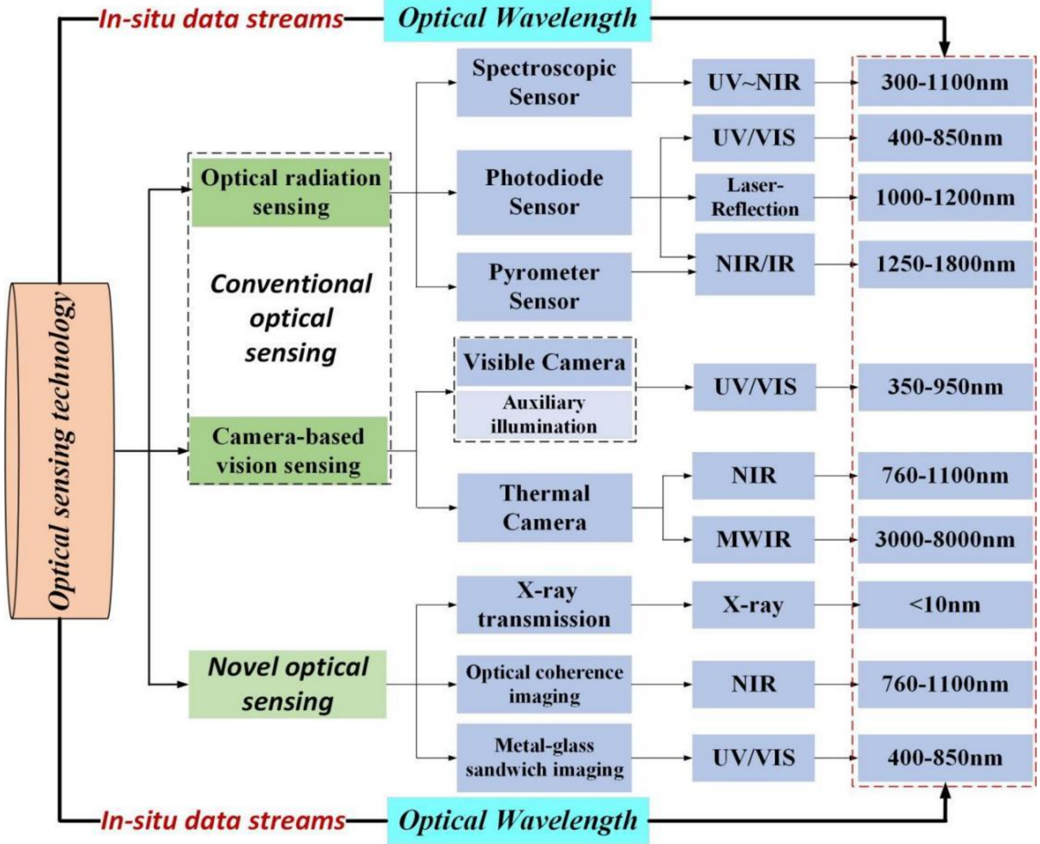

Fig. 5 In-situ optical sensing techniques in multi-wavelength during LBW process.

3.1 Optical radiation sensing

3.1.1 Photodiode-based sensor

Optical radiation signal mainly comes from the laser beam and welding area. The molten pool, spatters and plume can emit strong optical radiation ranging from various spectrum bands. In general, the optical sensors are distrubuted in multi-wave light emission: i) ultraviolet (UV) and visible (VIS) waveband (400-850nm), ii) laser-reflection waveband (1000-1100nm); iii) near-infrared (NIR) waveband (1100-1800nm) and medium-infrared (MIR) waveband (>4000nm) [22]. Particularly, the UV/VIS radiation comes from the atomic transitions and the bremsstrahlung within the plasma plume, and IR thermal radiation is emitted from hot melt pool [30].

Deduced from the amount of reported studies, the photodiode-based sensors are widely applied for real-time measuring vapor plume, reflected laser energy and thermal radiation. Photodiode sensors within UV/VIS, NIR and MIR ranges are commonly accepted in manufacturing industry due to a series of advantages of flexible configuration, simple structure and low cost. During laser overlap welding, three photodiode sensors were utilized to obtain independent information about the thermal (T-signal) condition of the molten pool, the radiation from plume (P-signal) and the back-reflected (R-signal) radiation of laser beam itself [29]. Fig. 6 shows the schematic of optical monitoring system and detailed optical radiation bands. They also suggested that the correlation between the T and P-signals is so strong that a T-P signal would be more useful than the raw T-signal in identifying the fluctuations in infrared radiation from the melt pool.

Table 2 Characteristics of different techniques applied for process monitoring

Sensor techniques	Monitoring objects	Sampling frequency	Facility cost	Technique advantages	Technique Limitations
Photodiode	Plasma plume Reflective laser energy Thermal	1~100kHz	Low	Flexible configuration, Simple structure, High sampling frequency High processing speed	Abstract one-dimensional signals, Low efficiency in detecting slight defects
Camera	Plasma plume, Melt pool, Keyhole	0.5~5kHz	Medium~ High	Abundance intuitionistic information about the process, Easy to understand the complicated process	Easy to disturb by the plume and spatters, Low sampling speed, High computing demands
	Melt pool	0.1-0.5	High		
Spectrometer	Spectrum of plasma plume	0.1-1kHz	Medium~ High	Flexible sampling Wider measuring spectrum range, High sampling resolution	Susceptible to interference of plume behavior, Poor real-time performance
Pyrometer	Temperature of melt pool	1-50kHz	Low	Temperature contactless measurement, Good capability of detecting radiation, High accuracy and speed	Hard to determine object emissivity, Limited capability of weld defects inspection
X-ray high-speed imaging	Inner keyhole and melt pool	1~10kHz	Extreme high	High spatial-temporal resolved information, Visualization of the process dynamics	Extreme cost equipment, Harmful to human, Difficult to apply in industrial field
Optical coherence tomography	Depth of keyhole	1~300kHz	High	Direct measurements of the keyhole depth, Suitable for industrial field, Strong anti-interference, fast response and robustness	Extreme cost equipment, Limited to the depth information of keyhole, Unstable measurement accuracy
Metal-glass “sandwich” imaging	Inner keyhole and melt pool	0.5~5kHz	Low	Low-cost and flexible configuration, Visualization of the process dynamics High sampling resolution	Approximately observation of inner keyhole and melt pool, Difficult to apply in industrial field

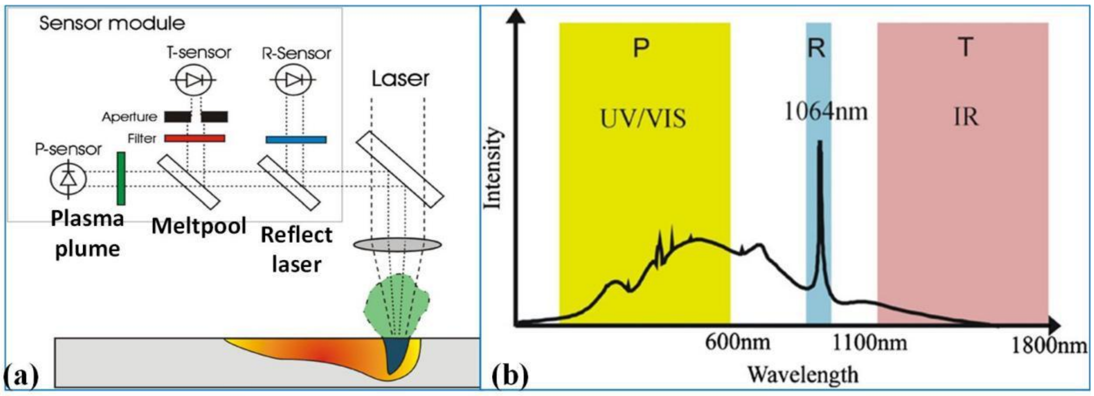

Fig.6 The schematic of optical monitoring system and different optical radiation bands [28].

According to recent studies [30]-[31], the effect of power density on the weld quality during laser welding process was considered. The co-axial back reflected and emitted light from the process zone was also measured using three optical sensors, each one measures the light emission in different spectral region (450-850, 1000-1200 and 1250-1700nm). From these optical sensors, the acquired signals were first applied as benchmarks to correlate with the weld quality and defects. By using photodiodes responsive to either visible or near-infrared emissions, a low-cost optical-based monitoring system was developed to relate the photodiode signals to various weld features, imperfections and process anomalies, in order to in-situ detect the high-power laser welding quality [35]-[36].

Considering the metal evaporation depends on weld penetration depth and bead width, it is suggested to apply the signals coming from the visible photodiode sensor to detect the variation of penetration depth and bead width. Accordingly, researchers attempted to adopt a multiple-sensor approach to make a more accurate identification on the spatial position of the plasma plume. For instance, Brocka' research team [33]-[34] have devised a photodiode sensing system that can help to detect plume position. Four same photodiodes were fixed at concentric positions to acquire the light radiation signals coming from different positions. They investigated the correlation between spatial light radiation and composite signals, and then determined the flow direction of metallic vapour plume. Due to the advantages of contact-free measurement principle and high sample rate, the photodiode-based optical sensing system has been commercialized for several years. As shown in Fig. 7, a laser welding monitor (LWM) system developed by Precitec company [32] can be easily installed on the laser head, and the detected radiation is guided through a beamsplitter to the optical sensor. When a high-quality weld is produced, the LWM system use a template to set threshold values for typical signal features (such as mean value) and then accept a pass or fail decision based on the given threshold values. However, this approach requires large amounts of high-quality welds to be produced and used as a template for each specific case, which might be a problem in low-volume production.

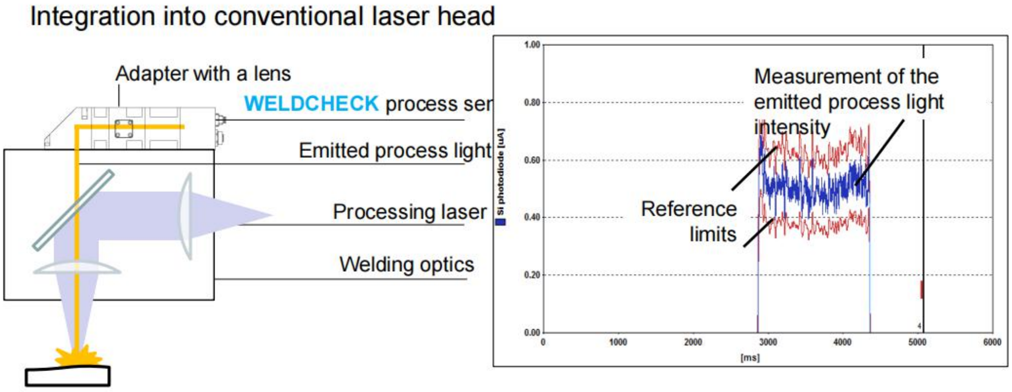

Fig. 7 The optical sensing system integrating into conventional laser head [32].

3.1.2 Spectroscopic Sensor

As is well-known, the spectroscopic sensor can monitor the emission spectra generated from laser-induced plasma for recognizing some welding defects because the plasma behavior contains a wealth of information about the laser welding process [38]. In order to infer the large amount of information deriving from the weld zone and enhance the possibility of distinguishing the source of welding defects, extensive researches attempted to adopt a spectroscopic sensor instead of a single photodiode. They applied the high-resolution monitoring solution to detect the laser-induced plasma and further investigate the relationship between the process parameters and radiation intensity of plasma plume.

In [37]-[40], by using the spectrometer equipping with a CCD detector array, the acquired spectrum signals emitting from the plasma plume were acquired analyzed to relate the temperature of the plasma electron and the weld penetration depth, and the research findings could provide a solid foundation for the development of a closed-loop control system. In an effort by Zhang et al. [32], the spectroscopic sensor was applied to gain a better understanding of the emission formation of plasma plume and in-situ detect the welding defects (i.e., blow out, undercut and humping) during the high-power disk laser welding process. In addition, Fig.8 [42] proposed a spectroscopic monitoring system to study the relationship between laser energy transmission and plasma plume during vacuum laser welding process of aluminum alloy, and then calculated the electron temperature/density of plasma plume based on the spectroscopic analysis algorithm.

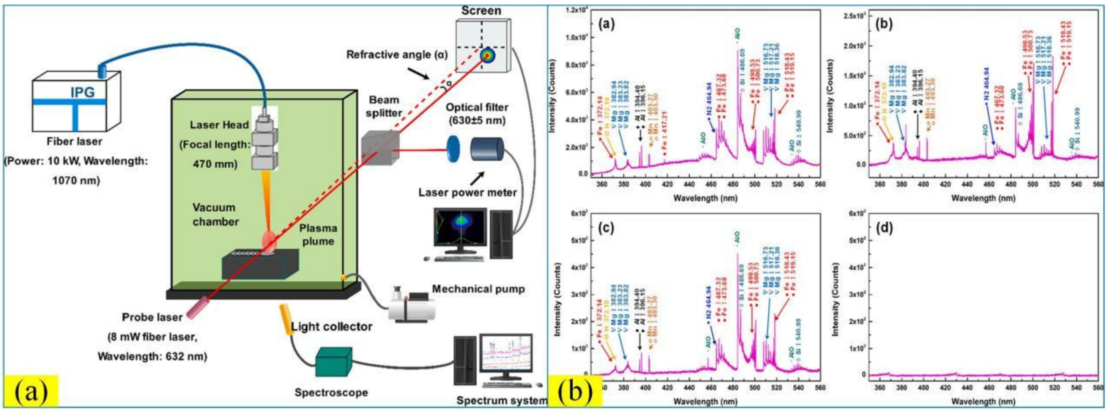

Fig. 8 The schematic diagram of the spectroscope measuring system (a) and plasma plume spectrums (b) during laser vacuum welding [42].

3.1.3 Optical pyrometer sensor

It is worth noting that the laser welding is fundamentally a thermal manufacturing process and the metallic material is melted by the high-energy laser beam. Thus, the thermal radiation signal is significantly strong in the welding zone, especially in the keyhole, molten pool and metallic vapor. Any variation of heat input should lead to a distinguishable conversion in the thermal radiation [43]. For the purpose of utilizing the transient temperature field in on-line monitoring and control, a fast-processing, cost-effective, steady and credible approach should aim to reduce the errors in temperature measurements. In current literatures, various types of detection sensors and systems such as thermocouples [44]-[46], photodiodes [47]-[48] and infrared cameras [49]-[51] have been proposed and compared. Unfortunately, they are generally not suitable for laser processing in a complicated industrial environment, since fast and precise measurements at each location are difficult to obtain in real-time. Moreover, the acquisition may be significantly affected by laser radiation and plume dynamics, depending on the fast heating and cooling rates of melted metal during the laser processing [54]. Instead, a valuable temperature monitoring technique referring to optical pyrometry is a non-contact measurement of a body based upon its emitted thermal radiation compared to a black body. Specifically, all objects above absolute zero emit thermal radiation, and the emissivity of the detected object needs to be obtained for a precis temperature measurement [52]. The spectral radiance of an ideal black body at different temperatures as well as the wavelength sensitivity range follows Planck's law [53], as shown in Fig. 9(a). Compared to the thermocouples at a fixed measuring point, the pyrometer have two excellent merits of temperature contactless measurement and good capability of detecting radiation emitted by moving melt pool, which helps overcome many obstacles.

Fig.9(b) [54] adapted a coaxial two-color pyrometer to monitor the laser welding process and discussed the dependence of the coaxial infrared temperature signal on penetration depth and weld width. The results indicated that the use of infrared radiation could be a promising tool for the temperature detection and weld quality control. Another work [55] has been reported a 3D-scanner with integrated pyrometer was designed to real-time monitor the temperature during quasi-simultaneous laser transmission welding of polyamide 6. By changing the laser power, the laser beam diameter and carbon black content in the lower polymer, the temperature information was acquired under different welding conditions. In addition, a two-dimensional ratio pyrometry [56] was combined to measure the thermal signal. It is proved that the emissivity and attenuation of thermal radiation were independent of two-dimensional temperature information. The proposed technique could be applied for calculating the melt pool diameter and latent heat, and validating the simulation based on FEM method. Although the optical pyrometer sensor has been widely applied in temperature monitoring, there exists some significant drawbacks such as the slow response time of measurement system and the intense interfere from hot plasma inside the keyhole.

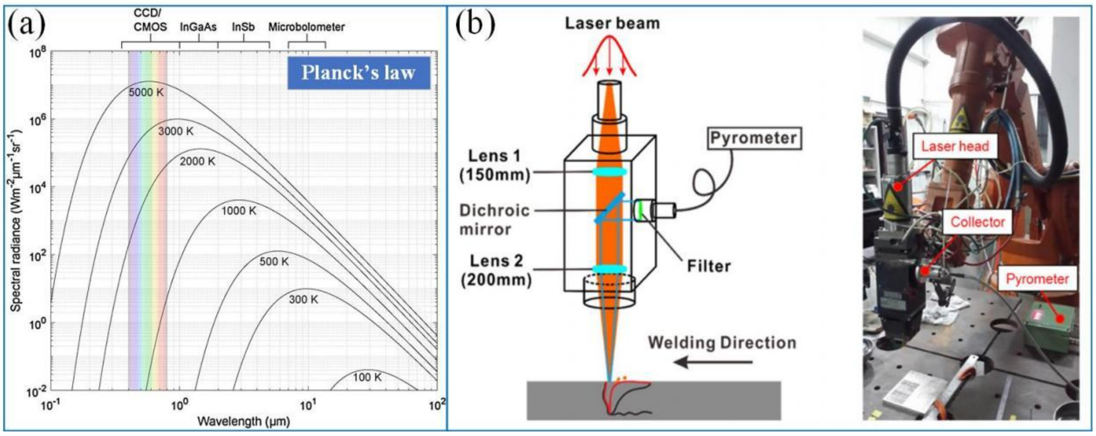

Fig. 9. (a) Spectral radiance of an ideal black body at different temperatures [53] and (b) coaxial temperature monitoring system with a pyrometer sensor [54].

3.2 Camera-based vision sensing

As mentioned above, the optical radiation sensing technique is only an indirect measure of the process dynamics with a very limited field of view. A direct camera-based observation of the interaction between laser beam and metal material does not suffer from these drawbacks. Nowadays, the camera-based monitoring technique is suggested to be one of the most intuitive methods due to the advantages of higher spatial measurement and yielding more detailed information [57]-[59]. Furthermore, it can in-situ monitor the dynamic behaviors of the melt pool and plume and accurately locate/identify the weld defects. Therefore, extensive research attempts have been made to utilize different visual sensors to obtain the in-process information during laser welding.

The mainstream sensors and in-situ data collection devices proposed in the literature can be grouped into three major categories: i) UV/VIS-camera, ii) NIR-camera and iii) MWIR-camera, which can capture the images of plume or molten pool based on optical radiation range during laser welding. A further categorization regards the sensor mounting strategy involving co-axial and off-axial systems. In co-axial configurations, the sensors exploit the optical path of the power source, whereas in off-axial configurations, the sensors are installed outside the optical path, with a suitable angle-of-view with respect to the region of interest. Table 3 summarized some reported work on the different types of visual sensing techniques for in-process monitoring of the physical phenomenon.

Table 3 Main set-up parameters proposed by authors for camera-based monitoring of LBW process (Melt pool: MP, Keyhole: KH, Vapor plume: VP, Spatter: SP)

Type	Target	Camera Type	Auxiliary Light	Resolution	Frame/fps	Year/Ref.
Co-axial	MP, KH	High-speed camera (Photon FASTCAM)	Semiconductor (808nm)	512×384	50,0000	2020/[63]
	MP, KH	CCD camera (Kodak KAI-0340)	Green LED light source (540nm)	648×488	210	2013/[60]
	MP	CCD camera (KP-F2A, Hitachi)	Green LED light source (532nm)	644×239	30	2012/[65]
	MP	High-speed CMOS camera	None	64×64	7915	2009/[66]
	KH	CMOS camera (DFK42BUC03)	Green LED light source (530nm)	1280×720	33	2015/[67]
	MP, KH	CMOS camera	Pulsed laser diodes (840nm)	1312×1082	200	2019/[68]
	MP	CMOS camera (MQ013MG-ON)	None	7.7μm/pixel	172	2020/[69]
	MP	CMOS VIS-camera and NIR-camera	None	320×256	160	2013/[71]
	MP	High-speed Tachyon 1024 MWIR-camera	None	32×32	-	2015/[72]
Off-axial	MP, KH	CCD Camera	None	659×493	200	2020/[73]
	MP, KH	NAC high-speed NIR- camera	None	-	1000	2014/[82]
	MP, KH	NAC high-speed CMOS camera	Diode laser light source (980nm)	512×500	5000	2014/[83] 2015/[84]
	MP, KH VP, SP	High-speed video camera	Diode laser light source (808nm)	-	5000	2013/[90]
	MP, VP and SP	NAC high-speed camera	None	512×512	2000	2014/[89]
	KH, VP	Photons A4 high-speed camera	Semi-conductor laser source (808nm)	-	20000	2018/[92]
	KH, VP	High-speed camera (Olympus, i-SPEED 3)	Diode laser light (808nm)	-	1500	2021/[91]

3.2.1 Co-axial visual sensing

Over the past decade, many scholars have designed and developed a co-axial visual setup system to monitor the dynamic behaviors of the melt pool and keyhole in laser welding. In [60]-[65], a co-axial monitoring system including a high-speed CMOS camera and auxiliary illuminant system was built to obtain the keyhole and molten pool images during conventional/remote lap laser welding, and then the melt pool width was calculated to identify the weld surface width and penetration status. Other reported studies [66]-[69] also applied the co-axial VIS-camera systems with external illumination to acquire the visual images and extract geometrical features from the auxiliary illuminated process zone, including keyhole area, weld pool area, weld width and background area.

Except for the laser keyhole welding, the work by Tang et al. [70] developed a real-time visual monitoring system comprising a CMOS camera and a coaxial assisted module of the laser head, and captured the the images of the molten pool in the passive illumination condition during laser surface melting (LSM) process. Fig. 10 [71]-[72] developed a coaxial monitoring system integrating VIS and NIR-camera without auxiliary illumination, and a real-time image processing system analyzes the camera images regarding welding irregularities and delivers information to characterize the weld process and its result. In laser lap welding, Lapido et al. [73] presented a novel approach for real-time monitoring evolution of the melt pool under several welding procedures by utilizing uncooled PbSe image sensors in the mid-wavelength infrared range.

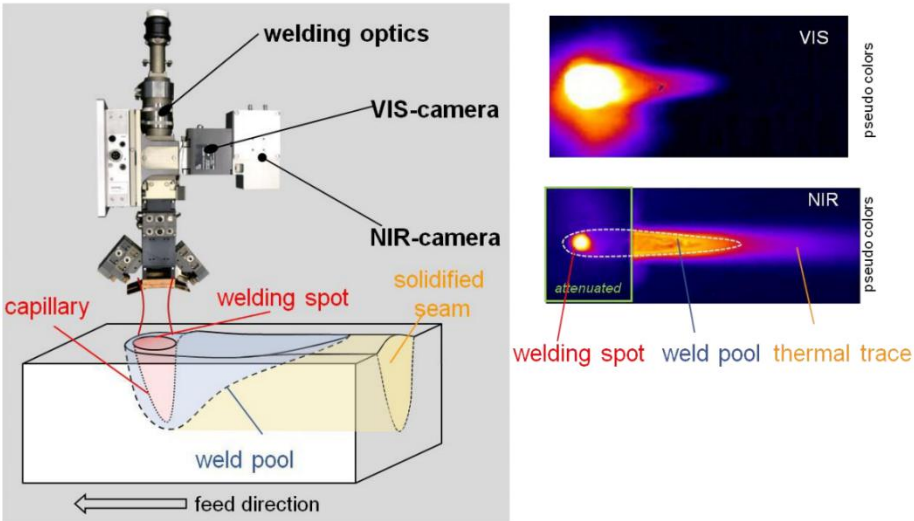

Fig. 10. The welding zone at deep-penetration welding consists basically of three areas: the capillary at the location of the welding spot, the liquid weld pool and the solidified seam [71]-[72].

3.2.2 Off-axial visual sensing

In contrast to the co-axial camera system, off-axial cameras with a more flexible angle can be developed to gather information about the keyhole and melt pool, as well as plume and spatters during LBW process. For instance, our research team have performed a series of long-term studies on the process monitoring of laser-based manufacturing, such as remote laser welding [74], pulsed laser spot/seam welding [75]-[76],[124],[202], laser-arc hybrid welding [77]-[79] and laser melting deposition [80]. By establishing an off-axial visual sensing platform consisting of the high-speed camera and laser illumination system, we can clearly capture the images of keyhole/melt pool and vapor plumes, and further investigate the metal melting/ solidification phenomena and the underlying mechanisms of the occurrence of welding defects (cracks and porosity), which as shown in Fig. 11.

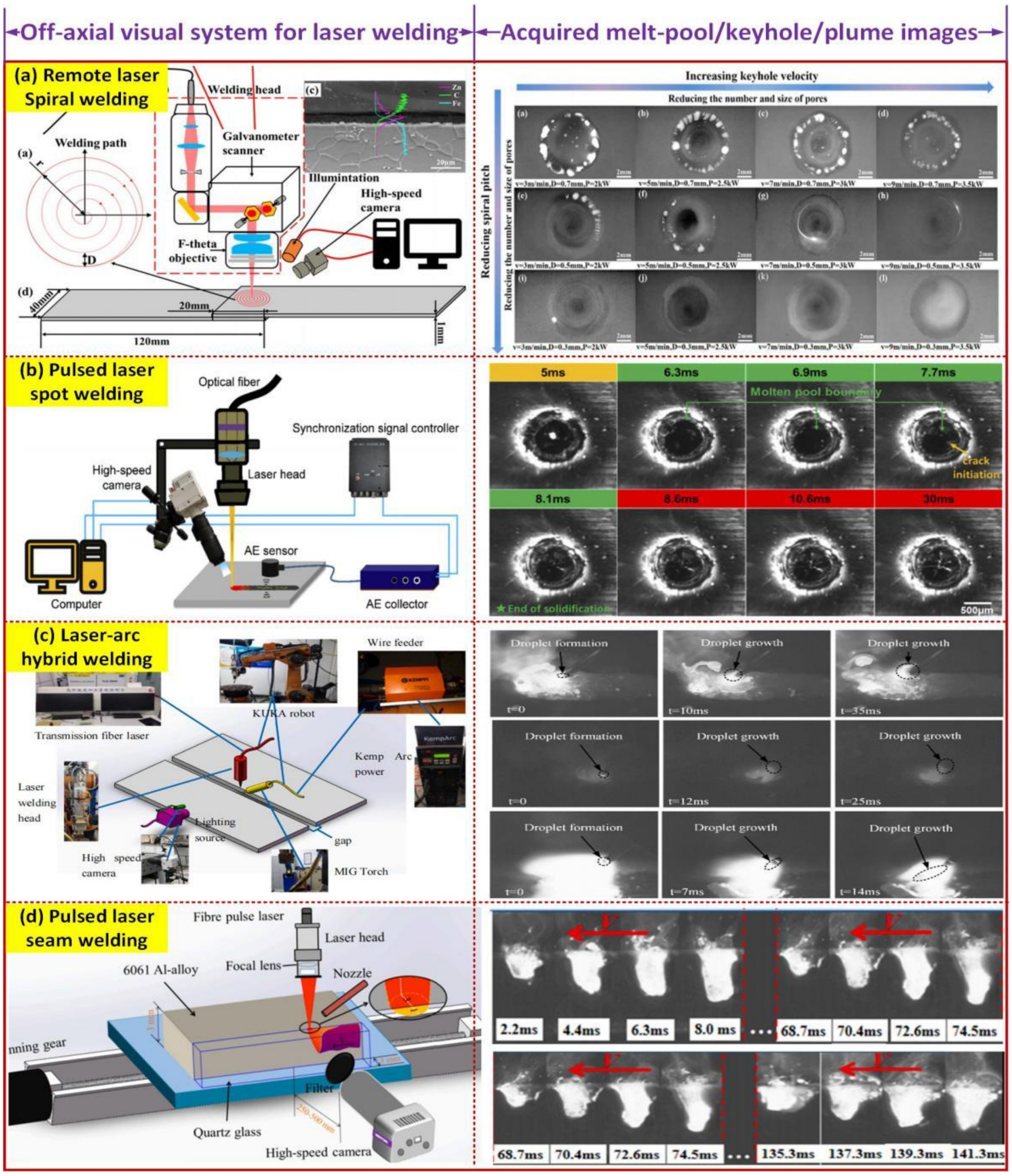

Fig. 11. The developed off-axial visual sensing platforms for capturing the images of keyhole, melt pool and plume for the laser-based manufacturing process: (a) Remote laser welding [74]; (b) pulsed laser spot welding [75]-[76],[202]; (c) laser-arc hybrid welding [77]-[79]; (d) pulsed laser seam welding [124].

Recently, the researchers [82]-[85] applied a high-speed NIR-camera with a narrow-band pass filter to capture the morphology of molten pool and its shadow behavior during laser welding. By analyzing the geometrical characteristics of molten pool shadow, the relationship between the morphology of molten pool and the LBW stability was investigated quantitatively. Another reported studies [88]-[90], [209] used two high-speed cameras in different wavelength to capture the vapor plume and spatters in high-power disk laser welding, the result shows that the measurement of UV/VIS-camera light was more appropriate for plume and spatter detection. Meantime, the high-speed NIR-camera was setup at the position of 60° to the horizontal direction to clearly monitor the behaviors of keyhole and melt pool. It has been found that the vapor plume/spatter and keyhole/melt pool characteristics have a close relationship with the laser power and the actual welding quality.

During the high-power fiber laser welding, a high-speed camera positioning laterally was adopted to observe the spatter and vapor plume behaviors, in order to better analyze the spatter formation mechanism[86]. Further, two high-speed cameras were synchronously utilized to investigate the 3D vapor plume fluctuations in overlap-joint of LBW. The results indicate that the position of the vapor plume contains the abundant information on the welding process [87]. To better observe the dynamic melt pool and vapor plume during laser oscillation welding, Li et al. [91] employed a off-axial visual sensing system. The width of plume is acquired in front of welding direction, while the height, area, and inclination angle are observed on the side of welding direction. Meantime, the high-speed camera and the diode laser source (808nm) are presented 70° in front of welding direction to clearly acquire the images of the melt pool images by eliminating the interferences of plume and spatter light. However, the camera-based sensors often suffer from heavy specular reflection and interference from laser-induced plasma plume. Thus, the external illumination system is required to heighten image quality, and the complex image processing algorithms hinder its further development in automatic welding manufacturing.

As an emerging monitoring method based on the Faraday magneto-optic effect, the magneto-optical imaging (MOI) is an integrative nondestructive method by using the magnetic-field information of the workpiece to visually test its surface/inner quality. Some reported works by Gao et al. [205]-[207] analyzed the principle of MOI technique for defect detection, which converts the magnetic field distribution into a MO visual image of natural weld defect during laser welding process. Further, Gao et al. [208] proposed a multi-directional MOI technique based on induced rotating magnetic field to solve the problem of directional detection of MO imaging under alternating magnetic field excitation. Multi-directional defect detection experiments clearly demonstrate the performance of the monitoring system under the rotating magnetic field excitation.

3.3 Multi-sensor fusion of optical radiation and vision

Typically, one single sensor is not sufficient to describe the complete and complex welding process, it has a rather low detection precision and can only identity a few kinds of welding defects. Therefore, multiple sensors and systems should be utilized to to gain overall knowledge of the welding process. The integration of visual, photodiode and spectrometer sensing method has become the research focus of laser welding monitoring in recent years, as it has the advantages of high sampling speed and great information capacity that help to provide comprehensive feature information of process detection. In previous research, Fig.12 [90] set up a four-signals detecting system that combines two visual sensors and two photodiode-based sensors. With an auxiliary illumination diode laser source (wavelength of 976nm), a visual sensor was applied for observing the geometrical shapes of keyhole and molten pool. Another visual sensor observed the formation of metallic vapor on top and bottom of workpiece. In addition, the two photodiodes were adopted for detecting the intensity of visible light emission and laser reflection. The proposed multiple-optics sensing system can help provide a comprehensive understanding and accurate diagnosis on high-brightness disk laser welding process. Wang et al. [93] combined an industrial

CCD camera and a spectrometer to simultaneously monitor the ARM laser welding of stainless steels. The process characteristics of the keyhole entrance was observed by the CCD camera, and the length, width and area also were quantified by the selected image processing method. Furthermore, the intensity of metallic vapor and plasma was obtained with the aid of the proposed spectrometer system, and then the relationship between the keyhole entrance geometry and the plasma intensity was analyzed correspondingly. The work by Kong et al. [94] also developed a real-time monitoring system integrating with a high-speed CCD camera and Ocean-Optics spectrometer to visualize the dynamics of the molten pool and plasma plume in laser lap welding of galvanized high strength steel.

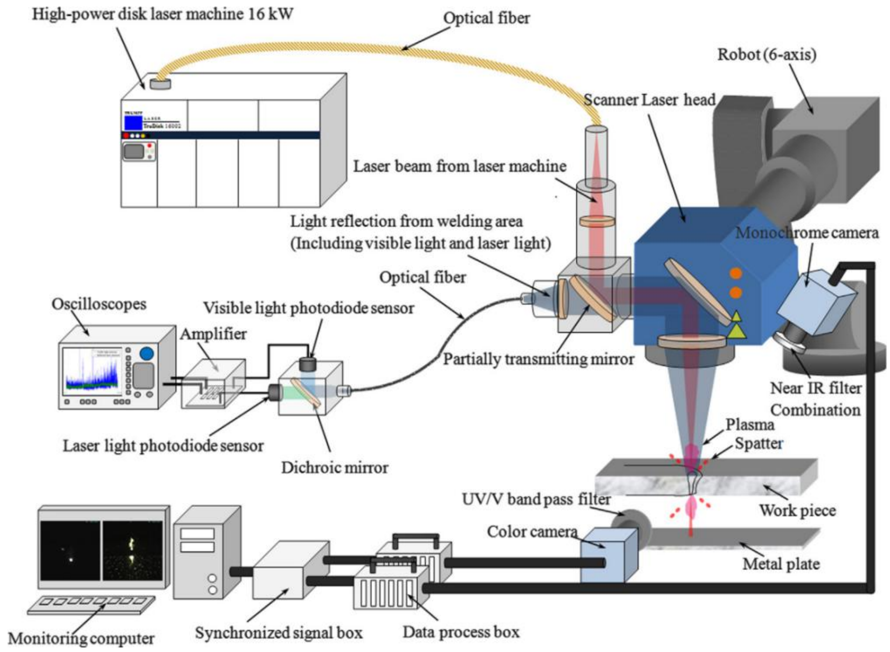

Fig.12. Schematic of multiple optics sensing of disk laser welding [90].

The Kaplan' team [95]-[96] have focused their research on the multi-feature analysis of weld defects by combining a photodiode sensor (developed by Precitec LWM) with a visual sensor. The results concluded that the photodiode sensor is more efficient in identifying weld penetration, while the camera yields more accurate results for detecting some typical defects of blowout, undercut and humping. Furthermore, the intensity of metallic vapor and plasma was obtained with the aid of the proposed spectrometer system, and then the relationship between the keyhole entrance geometry and the plasma intensity was analyzed correspondingly.

3.4 Novel optical sensing methods

As mentioned previously, the optical radiation and vision sensing techniques mainly focus on monitoring the dynamic behaviors of the keyhole, melt pool and vapor plume in the top view. However, it is not possible to directly observe the internal keyhole and melt pool inside the metal which essentially determine the final welding quality. Furthermore, the conventional optical-sensing techniques can provide only minimal depth information and may be blinded by the intense emission of metallic plasma and spatters. To gain insight into the process dynamics phenomena including the shape and geometry of the capillary (keyhole) in the weld bead, some novel monitoring methods including X-ray imaging technique [97]-[110], inline coherent imaging [111]-[117] and metal-glass “sandwich” imaging [118]-[123] have been proposed and achieved excellent results in laser beam welding. Next sections, we summarize and analyse the research progress of the novel monitoring techniques.

3.4.1 X-ray high-speed imaging

The inline x-ray imaging is a well-established methodology for observing the keyhole behavior with side view through the material. It can help acquire the high spatial-temporal resolved information of the keyhole behavior and inner defects (e.g. porosity) during the welding process. In earlier years, Katayama et al. from JWRI [97]-[98] carried out the X-ray in-situ observation during laser welding to reveal the mechanisms of the keyhole behaviour, bubble formation and melt flow inside the molten pool. Meantime, Matsunawa's [99]-[104] group carried out other experimental investigations to observe the dynamic keyhole shapes in deep penetration laser welding by X-ray transmission imaging systems with a high-speed video camera. Unfortunately, most of the obtained inner keyholes were not clear enough for further quantitative analysis.

Recently, the Institut für Stahlwerkzeuge (IFSW) designed a X-Ray high-speed imaging system to in-situ monitor the laser welding process at a high frame rate (up to 10kHz) [106]-[108]. As shown in Fig. 13(a), it consists of three main parts: the processing area including the sample and processing-optics, the X-Ray tube and the imaging system. The typical X-Ray image of a capillary (keyhole) in laser welding can be acquired, as shown in Fig. 13(b). The X-ray system was successfully applied to in-process measure the keyhole shape in laser welding of stainless steel. Shevchik et al. [109]-[110] also used a high-speed hard X-ray radiography to directly visualize the dynamical behavior of the melt pool inside the metal workpiece during LBW process. The observation results are crucial to establish the ground truth of the events that were adopted to define the different types of welding quality.

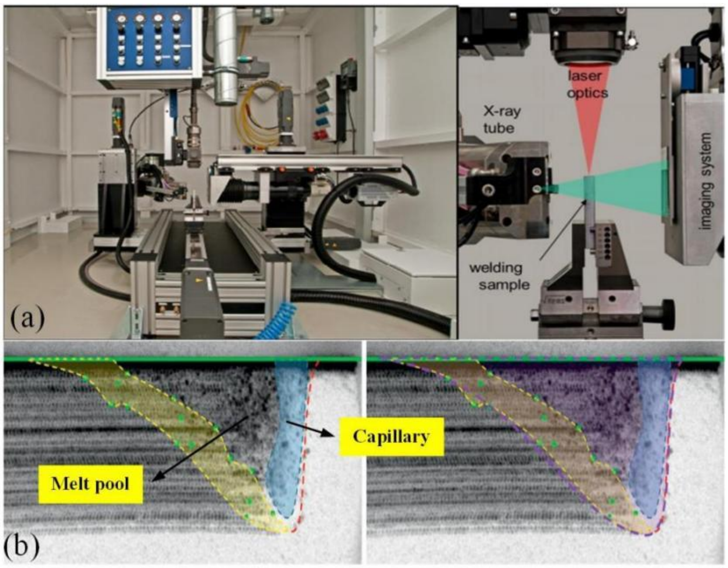

Fig. 13 (a) Facility for welding experiments with online X-Ray observation and (b) Typical X-Ray image of a capillary laser welding process [106].

3.4.2 Optical coherence imaging

As noted above, the X-ray imaging system is capable to gain intuitive information about the keyhole geometry such as size and shape. However, the laser welding process is a highly dynamic process with obvious changes in a very short time (less than 0.1ms). Since the keyhole is believed to be filled with metal vapor, its optical extend can be measured by applying the optical measurement system. Recently, the optical coherence tomography (OCT) proved to be a good choice in laser processing due to a tiny measuring intensity [111]. Therefore, the Precitec GmbH successfully developed an In-process Depth Meter (IDM) system to real-time measure the capillary depths [113]. It operates at a wavelength of 1540nm with an output power and the measurement rate is up to 70kHz with an axial precision of 10μm. Also, the OCT technique with a IDM sensor could achieve the adaptive penetration depth control in fillet lap joint during remote laser welding (RLW) according to [115]. To further improve the sampling frequency and temporal resolution, Queen's University have developed a Laser Depth Dynamics (LDD) monitoring system based on inline coherent imaging (ICI) [116]-[117] which provides direct geometrical measurements of the keyhole depth and associated dynamics at rates>300kHz in comparison to the X-ray frame-rate at 1 to 10kHz. The technique is closely related to spectral-domain optical coherence tomography (SD-OCT) and is delivered through a camera port and combined co-axially with the process beam. ICI simultaneously resolves backscatter from multiple depths along the laser processing beam path, and is robust to all other optical signals (machining light, plasma, black-body radiation, and so on) due to its inherent spectral filtering and coherent time gating.

3.4.3 Metal-glass "sandwich" imaging

In general, the X-ray imaging technique is costly and harmful, and the OCT technique is also expensive and only obtain the keyhole depth information. Therefore, Zhang' research group firstly [118] developed a low-cost and flexible sandwich method which is an aluminum workpiece clamped in between two pieces of transparent glass. It can clearly observe the inner keyhole in deep-penetration laser welding and help provide an effective way to analyze two main absorption mechanisms of Fresnel absorption and Inverse-Bremsstrahlung absorption exist in the keyhole. Then a modified sandwich was proposed specimen including one sheet of stainless steel and one piece of GG17 glass, in order to intuitively observe the keyhole during laser welding with a 10-kW fiber laser [119]. In addition, Wu et al.[120]-[122] both applied a steel-glass sandwich method to clearly observe the keyhole behavior, spatter, and keyhole-induced bubble formation in laser welding. The observation results revealed the the formation mechanisms of the spatter and bubble and then discussed the relationship between the spatter and bubble formation. Zou et al. [123] used the metal-glass sandwich imaging method to observe the laser-induced intense evaporation vapor on the keyhole wall, in order to analysis the interaction processes between the laser beam and keyhole wall.

The above-mentioned works mainly sought to elucidate the interaction mechanism between the laser beam and keyhole wall, keyhole instability and weld defects in continuous-wave (CW) laser welding of thick-plates. In pulsed-wave (PW) laser welding of thin-sheet, our research group [123] have applied a high-speed imaging (HSI) system for directly monitoring the dynamic behavior of inner keyhole with the aid of a transparent glass under different parameters. The observation results indicate that the weld penetration depth is determined primarily by the variation of the keyhole depth/inclination angle and partly by the molten pool flow around the keyhole bottom.

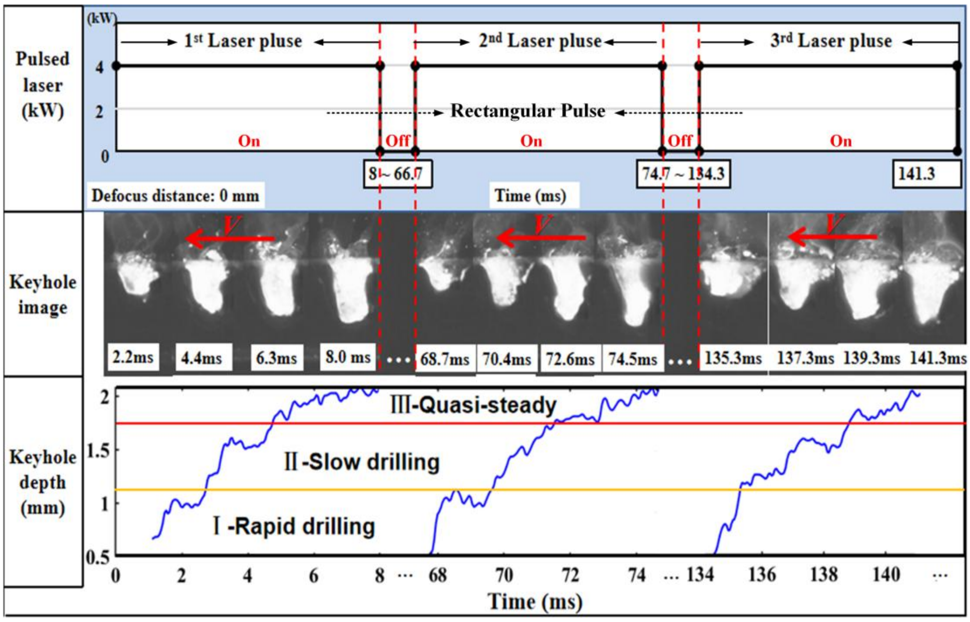

Fig.14 The keyhole depth fluctuation during pulsed laser welding based on metal-glass "sandwich" imaging technique [123].

4. Behavior characterization technology

According to Section 3, the application of multiple sensors has provided large amount of original data (signals or images) for laser welding monitoring. In order to quantitatively characterize the laser physical phenomenon (keyhole, melt pool or plume), it is necessary to extract the key measurement characteristics (*KMCs*) by means of the advanced image/signal processing algorithms. These extracted features that describe the significant characteristics of occurring phenomenon are required for classical supervised learning algorithms and are often manually designed and depend on signal types. The extraction of the meaningful features, such as spatial, temporal or spatial-temporal features is the foundation of new non-destructive quality inspection methods, which has been and remains a growing interest in manufacturing industry. This section provides a literature review of the advanced processing algorithms based on optical radiation and vision sensing techniques, and the detailed classification is depicted in Fig. 15.

4.1 Optical Imaging processing

In the visual monitoring system for laser welding process, the imaging processing plays an important role in obtaining the key visual features of welding phenomenon accurately. The literature devoted to optical imaging processing is summarized in Table 4 with respect to the geometric and statistical features.

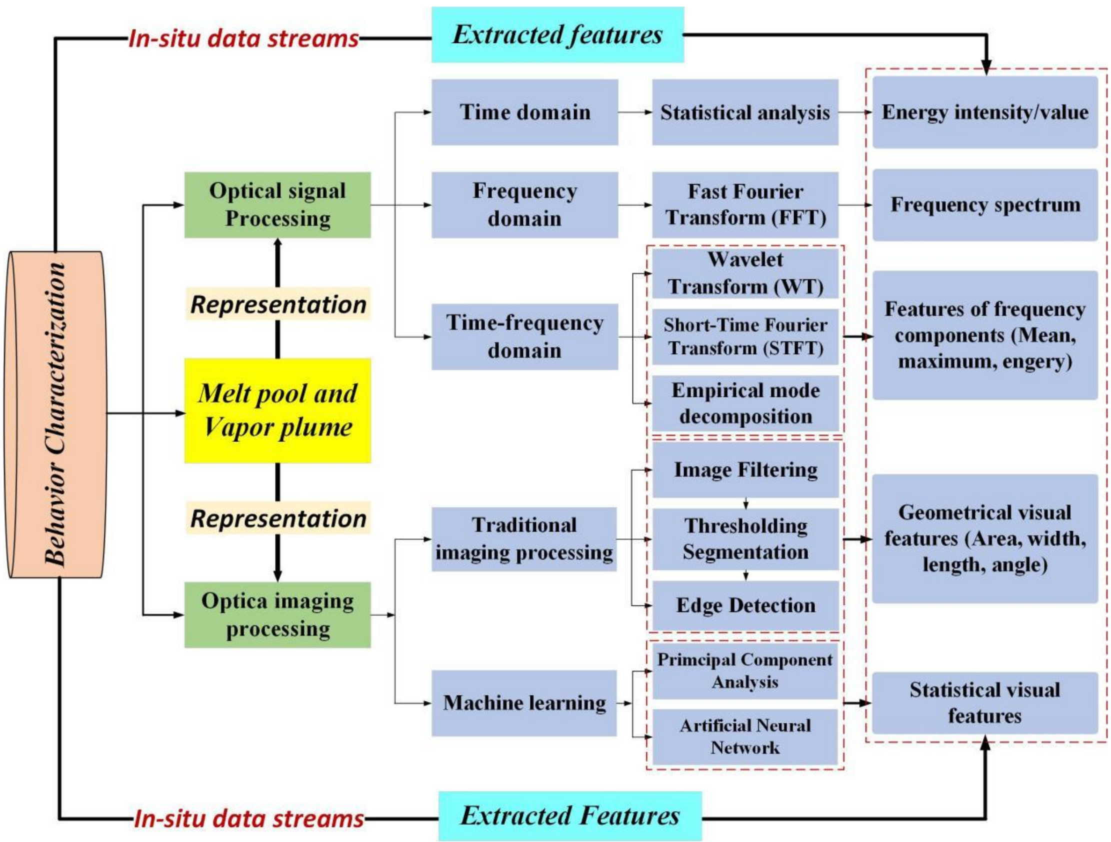

Fig. 15 Overall classification of behavior characterization techniques during LBW process.

Table 4 Feature extraction based on imaging processing methods of laser welding

Original data	Extraction technique	Extracted features (KMCs)	Year/Ref.
UV/visible images of plume and spatters	Image segmentation and gray-scale processing and Karhunen-Loeve transform	Plume size, plume growing direction, spatter radius, ejected direction and velocity	2014/[89]
Visible images of melt pool	Hybrid adaptive keyhole detection algorithm	Average gray value, area, and perimeter of keyhole	2020/[62]
	Image enhancement, edge detection and morphology segmentation	Area, maximal width and the tilt of the molten pool shadow	2014/[83], 2015/[84]
	Otsu's method, Canny edge detection, binarization	Area of keyhole and width of melt pool	2020/[125] 2020/[81]
	Gray projection distribution and the Poisson extinction method	Shape characteristics and area size of keyhole and full penetration hole	2012/[65] 2020/[127]
	Image segmentation based on CNN model	Keyhole area, weld pool area and weld width	2019/[69]
Infrared images of melt pool	Improved homomorphic filtering algorithm based on Fourier transform	Melt pool width	2014/[82]
Visible images of melt pool	Principal components analysis (PCA)	Salient statistical features of melt pool	2009/[66] 2015/[73]
	Deep neural network (DNN) Convolutional Neural Networks (CNN)		2016/[128] 2020/[129]

4.1.1 Geometrical features extraction

Typically, feature extraction in LBW applications is firstly performed by using geometric information about the physical phenomenon. Conventional image processing techniques including threshold segmentation, morphological operations and masking are generally applied to extract the geometric features of melt pool or vapor plume. Fig.16 [125] acquired the laser welding images of molten pool through the coaxial monitoring system and adopted the gray-scale processing and binarization to extract the geometric features of molten pool including the length, width, trailing angle and area.

By applying the same coaxial observing system, a hybrid adaptive detection algorithm was developed to segment the keyhole region and then extract/select ten key geometrical features for describing the weld penetration status based on the wrapper algorithm [62]. To improve the capacity of resisting disturbances (i.e., strong plume and spatters), an improved homomorphic filtering algorithm based on Fourier transform can be applied to analyze the infrared image characteristics and calculate the melt pool width [82]. In addition, a conventional image-processing method was proposed to extract the visual features of laser-induced plume and spatter including the plume size, plume growing direction, spatter radius and spatter ejected direction, which are closely related to the final laser welding quality [89].

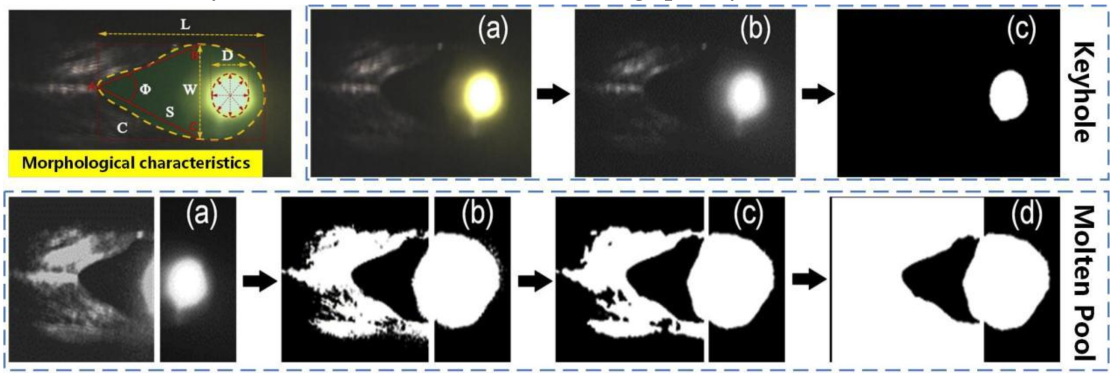

Fig.16 The image process procedures of the molten pool and keyhole [125].

4.1.2 Statistical features exaction

As described earlier, the advantage of geometric features in industrial applications are meaningful and easily interpretable, which can directly reflect the physical characteristics of melt pool and plasma plume. Nevertheless, it is inevitable to reduce the huge amount of theoretically possible features (e.g. shape and moment based features) with expert knowledge. In contrast to the geometrical features extraction, a principle component imagery (PCA) was firstly to extract appearance-based features from the raw images, which can be considered as a high-dimensional feature vector while every single pixel represents a feature [66]. The proposed machine-learning algorithm can reduce the feature space by removing redundant information based on a statistical approach compared to geometrical feature extraction. Lapido et al. [73] also used the PCA algorithm for decomposing the high-dimensional space of the MWIR images in a subspace of orthogonal components of maximum variance, which is closely related with the melt pool geometry in laser welding. However, the disadvantage of PCA method for feature extraction is less generally valid and more sensitive to variations of the experimental set up than geometry-based features. Recently, an auto-encoder based on deep neural networks was applied to extract salient, low-dimensional features from the high-dimensional laser welding data, which are used as input to a temporal-difference learning algorithm to acquire important real-time information about the process of laser welding [128]. Moreover, the study work by Gonzalez-Val et al.[129] presented a novel approach ConvLBM to monitor Laser welding processes in real-time. ConvLBM uses a convolutional neural network (CNN) model to extract meaningful features and quality indicators from raw MWIR coaxial images.

4.2 Optical signal processing

Except for the imaging process techniques, this section also reviews the recent research and development of optical signal processing. Generally, the signal processing includes three types: i) time domain analysis, ii) frequency domain analysis, iii) time-frequency domain analysis, which are summarized in Table 5.

4.2.1 Time domain analysis

Considering the acquired optical signal itself is a time evolution of non-stationary signal, the feature extraction in time-domain is the most nature and direct method of analyzing the physical phenomenon which is to take time t as independent variable [130]. Any signal evolution or local transition in the time domain can be related respectively to process variation or to local macro/micro weld defects. Thus, a fault detection algorithm is proposed and analyzed based on the time domain comparison between the acquired signals and the reference signals, in order to real-time monitor the laser welding process and diagnose the potential defects.

In earlier years, Park et al. [131] applied the UV and IR photodiodes to measure the variation of plasma and spatter in CO_2 laser welding and obtained the data number deviating from the reference signals in time-domain analysis method, in order to provide the key performance indicators for identifying the actual welding quality. With the same photodiode (UV and IR) based monitoring system, Bardin et al. [132] calculated the statistical feature of spike amplitude, which shows a more limited correspondence with the imminent opening of the keyhole in full-penetration laser welding. According to the studies from Lee et al. [133], an approach using AI-algorithms was adopted for efficiently extracted the time-domain features of the spectral information. The zinc and iron emission lines were pre-processed using statistical features including the mean, root mean square, standard deviation, peak, skewness and kurtosis. Based on the process data, the Fisher's criterion was then applied to rank several features for selecting the most valuable features. During remote laser welding (RLW), the commercial LWM 4.0 system was applied to acquire three types of photodiode-based signals (plasma plume, thermal radiation and reflected laser light). The signal processing methodology is based on the evaluation of the energy intensity and scatter level of the acquired signals, which can provide key information about optical radiation emission and the inherent process variation [134].

Table 5 Feature extraction based on signal processing methods of laser welding

Analysis method	Optical signal	Extraction technique	Extracted features (KMCs)	Year/Ref.
Time domain analysis	Optical emission in UV/VIS and IR	Statistic energy analysis	Energy intensity and local signal scatter	2021/[134]
			Data number deviated from reference signals and standard deviations	2002/[131]
			Spike, Pearson correlation, mean value and variance	2005/[132]
	Plasma spectroscopy	Statistic analysis	Electron temperature and its standard deviation	2007/[135] 2012/[136]
		Statistic analysis and Fisher's criterion	Ranked statistic features	2020/[133]
Frequency domain analysis	Optical emission in UV/VIS	Discrete Fourier Transform	Frequency spectrum characteristic	1997/[137] 2012/[138] 2013/[139]
		Fast Fourier Transform (FFT)	Maximum frequencies per time	2009/[140]
		Power spectrum	Number of peaks and peak frequencies	2021/[142]
Time-Frequency domain analysis	Laser back reflection and optical emission	M-band wavelets	Relative energies of narrow frequency bands	2019/[143]
	Optical emission in UV/VIS	Discrete wavelet transform (DWT)	Frequency Components	2010/[144] 2021/[147]
	Optical emission in UV/VIS	Orthogonal Empirical Mode Decomposition And Teager-Kaiser Energy Operator	Amplitude and frequency of IMF components	2008/[149]
	Optical emission in UV/VIS	Short-Time Fourier Transform	The high frequency component	2009/[148]
	Optical emission in UV/VIS	Winer-Ville distribution	Amplitude and frequency of components	2019/[150]

4.2.2 Frequency domain analysis

Although the time-domain characteristics of optical signals can describe the changes of welding process to some extent, it is not enough to fully reveal the intrinsic features of optical signals. Since the frequency-domain analysis is a more accurate and efficient analytical approach, lots of research has been carried out on the frequency features of optical signals in order to specify the correlation between signal frequency and the periodical changes of the molten pool. Once the correlation is specified, the frequency features of the characteristic signals can be easily identified when some welding defects occurred.

Earlier study [137] applied the Fourier Transform (FT) method to investigate an oscillatory intensity modulation of the optical signals, which mainly originates from the oscillation behavior of keyhole and melt pool during laser welding process. The analysis results indicate that the spectral content of acquired signals could be applied to detect a fully open keyhole and to determine the weld penetration depth in real-time. The reported work by Mrna et al. [138]-[139] presented new findings about the correlation between the keyhole depth and the frequency characteristics of light intensity oscillation by using a discrete Fourier transform algorithm. The results revealed that the lower frequency components correspond to melt pool oscillation of the melt pool while the higher frequency components correspond to the plasma plume oscillation. By applying the same FT algorithm, Schmidt and his research staff [140] have pointed out that the frequency of melt pool oscillation is within the range of 300-500Hz, while that of the keyhole oscillation is within the range of 2000-2500Hz in case of a 3.6kW laser lap welding process. In addition, Colombo et al. [141] investigated the optical monitoring of the laser welding on titanium alloy workpiece. It has been concluded that the time-domain features of the visible and infrared light signals mainly reflect the welding defects (e.g. lack of penetration, undercut and humping). Also, the strong keyhole fluctuation easily occur when the frequency of visible light signals is within the 160-2400Hz range.

4.2.3 Time-frequency domain analysis

As is well-known, most of the acquired optical signals in manufacturing industry are represented in the time or frequency domain. For stationary signals there is no need to go beyond the time or frequency domain. However, the mono-dimensional solutions (time or frequency) are not sufficient in dealing with the non-stationary signals during the fluctuating laser welding process. Therefore, some common time-frequency analysis techniques including Short-Time Fourier Transform (STFT) , Wavelet Transform (WT), Wigner-Ville Distribution (WVD) are suitable to analyze the non-stationary and nonlinear optical signals. Fig.17 [148] has investigated the frequency characteristic along the time axes by using short-time Fourier transform method. The higher frequency component (4.8-12kHz) of the optical radiation signals increases greatly when welding defects occur. This provides a reliable basis for accurately detecting and positioning the welding defects, which as shown in Fig. 17.

Researches carried out by Giuseppe D' et al. [149]-[150] proved that the time-domain analytical approach based on the Winer-Ville distribution (WVD), orthogonal empirical mode decomposition (OEMD) and Teager-Huang Transform (THT) are more effective than traditional time or frequency domain processing methods when used for locating welding defects such as the incomplete penetration (0.5-2mm) and porosity (0.2-1mm). As it mentioned above, the signals generated during the changing welding process are non-stationary, an important time-frequency method based on wavelet transform (WT) algorithm is suitable for investigating the time-varying phenomenon, which decomposes the signals into different frequency bands and allows consequent easier extraction of key features related to weld quality.

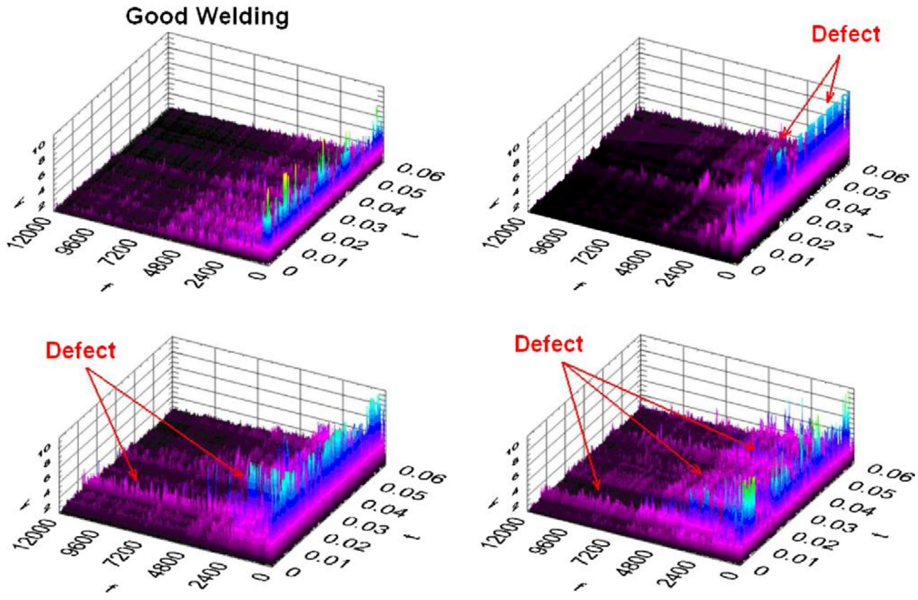

Fig.17 Defects detection in time-frequency analysis during laser welding [148].

Fang et al. [146]studied the spectra of the optical signals emitted by plasma during CO_2 laser welding by using wavelet analysis. The results show that the wavelet analysis can decompose the optical signals, extract the signal characteristics and diagnose the defects location accurately. Sibillano et al. [144] applied the discrete wavelet transform (DWT) to decompose the optical signal into various discrete series of sequences over different frequency bands. The proposed DWT method is capable of providing the time-frequency information simultaneously, in order to reveal a correlation between the optical frequency components of the plasma plume oscillation and the weld penetration depth. In [152], the same DWT method was also proposed to analyze the signals within the time-frequency domain. The detail signals at different decomposition levels disclosed the essential information with regard to the modes of laser welding process. Accordingly, the deep penetration welding (keyhole) was clearly distinguished from the shallow (conduction) welding mode. In addition, the wavelet packet decomposition and principal component analysis (WPD-PCA) were carried out to extract feature parameters of both high-frequency photodiode signals and low-frequency spectrometer signals, which could perform laser welding process monitoring and welded defect diagnosis [153].

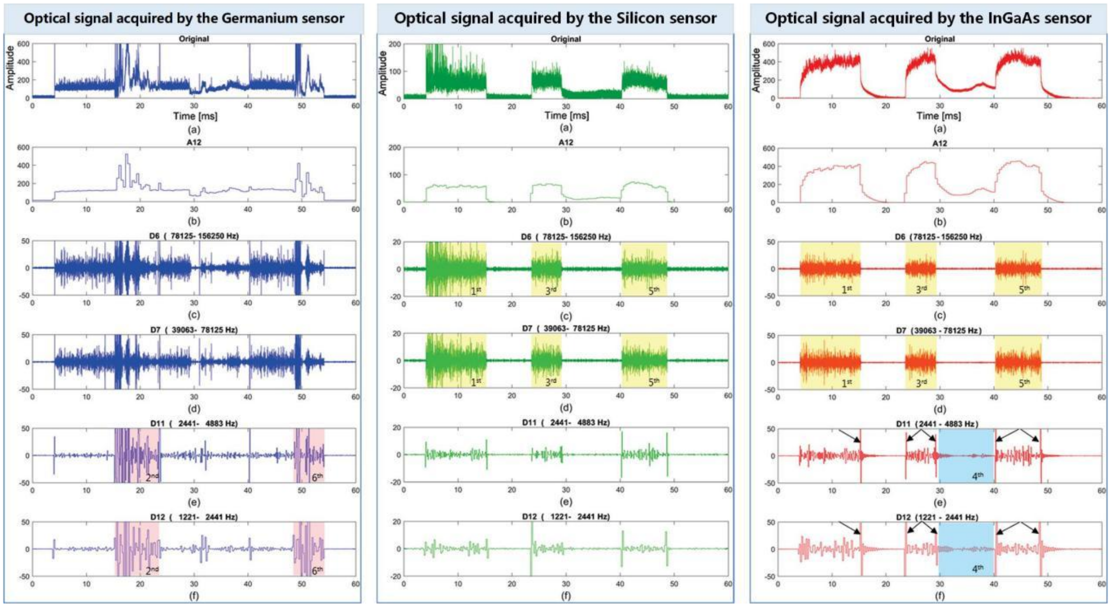

Fig.18 Wavelet decomposition of the optical signal acquired by the different sensors for several decomposition levels [152].

5. Machine-learning model technology

As it mentioned earlier, the gathered signatures of the melt pool and plume can be observed and correlated with quality-related phenomena occurred during the laser welding process. Unfortunately, the correlations of these signatures to certain quality criteria (referring to *KPCs* in Sec 2.3) are often ambiguous and they are not sufficient to directly measure addressed *KPCs* as an indicator of weld quality, so that statistical proof of welding quality by a series of destructive tests is necessary [159].

Due to high dynamics of melt pool and plume, an approach based on precise physical modeling of the welding process is not suitable for real-time quality diagnosis. To date, almost predictions for LBW process are based on multi-physics numerical simulation that are very difficult to solve and represent high computational burden. In contrast, the use of machine learning techniques can reduce the dependence on in-depth understanding of the LBW process and make extracting valuable information from measurables easier. As such, recent development led to advanced process monitoring systems which integrate the machine learning (ML) techniques for weld formation prediction and defect diagnosis, in order to optimize/control the weld quality. In this section, we mainly review the comparison of classical machine learning methods and modern deep learning architectures with respect to prediction performance. Table 6 outlines the machine learning techniques for obtaining *KPCs* with classical ML and deep learning methods in laser welding process.

Table 6 Machine learning techniques for obtaining KPCs during laser welding
(RSE: Relative standard error, Acc: Classification Accuracy R^2: Adjusted R Square)

Method	Input (*KICs/KMCs*)	Output (*KPCs*)	ML techniques	Performance	Year/Ref.
Classical ML	Welding parameters and keyhole geometry	Penetration depth and keyhole tilting angle	RBF neural network	RSE (0.08~0.15)	2015/[67]
	Keyhole geometric features	Weld Penetration status	Wrapper and Random Forest	Acc (98.53%) AUC (0.999)	2020/[63]
	Melt pool geometric features	Good weld, weld width exceeded, lack of fusion, and undercut	Random Forest classifier	Acc (99.9%)	2018/[166]
	Keyhole geometric features	Good weld,lack of fusion, burn through,porosity	Hidden Markov Model	Acc (93.27%)	2020/[127]
	The relative energies of frequency bands	No illumination, conduction welding, porosity	Support Vector Machine	Acc (85.9%~99.9%)	2019/[143]
	DC/AC components of radiation intensity	Penetration depth and bead width	Artificial Neural Network	R^2 (0.929) RSE (0.137)	1999/[170]
	Process parameters and OCT data	Poor and good welds	Artificial Neural Network	Acc (81.8%)	2020/[172]
	Intensity of three photodiodes	Poor and good welds	Fuzzy Logic pattern	Not mentioned	2001/[171]
Modern deep learning	MWIR/NIR Images of melt pool and keyhole	Good, lack of fusion, Sagging, lack of penetration	CNN+GRU (Classification)	F1-Score (0.938) Acc (93%)	2021/[188]
	Time-frequency spectrum graphs	Porosity defects categories (No and Yes)	CNN (Classification)	Acc (90%)	2021/[190]
	Images of melt pool and keyhole			Acc (96.1%)	2020/[191]
	Keyhole aperture image	Laser absorptance	ResNet (Regression)	R2 accuracy of 99.76%	2021/[192]
	Images of melt pool and keyhole	Penetration status (PP, MP, FP, EP)	CNN (Classification)	Acc (94.6%)	2020/[185]
	Wavelet spectrograms image of LBR signal	Conduction welding, stable keyhole, unstable keyhole, blowout and pores	CNN (Classification)	Acc (71-99%)	2020/[193]
	MWIR images of melt pool	Good or defective welds	CNN (Classification)	Acc (96.8%) F1-score(0.975)	2020/[129]
	Features from multi-sensor information	Sound, blowout, humping and undercutting	DBN (Classification)	Acc (96.93%)	2019/[194]
	Images of melt pool	Quality categories (Humping, no-humping)	CNN with PSO (Classification)	Acc (100%) R2 (0.957)	2021/[195]

5.1 Classical machine learning method

In laser-based manufacturing field, such data-driven approaches have been extensively studied in the past and are based on autoregressive exogenous (ARX) model [154]-[155], cluster analysis [156], fuzzy logic (FL) [156]-[161] or on supervised learning algorithms including multivariate regression (MR) [162]-[163], multi-layer perceptron (MLP) [164]-[165], and decision trees (DT) [166]-[167], as well as K-nearest neighbors (KNN) [168]-[169]. Once the eigenvector has been established, effective identification and classification of different welding status or defects can be realized by using advanced modeling technology. In general, fuzzy logic technology is considered one of the most widely applied technologies for welding detection. Based on the different photodiode signals (UV and IR), Park et al. [171] has proposed a fuzzy pattern recognition system, which can help to distinguish desirable weld seam from the bad one and recognize the causes of weld defects, such as low heat input, focus misalignment, gap mismatch and nozzle deviation. Meantime, they also proposed and compared the multiple regression analysis and neural network algorithms in estimating the penetration depth and bead width with the acquired photodiode signals [170].

In keyhole laser welding, Luo et al. [67] used a coaxial monitoring system to observe/calculate the keyhole geometry from the top side, and then adopted a radial basis function neural network for estimating the penetration depth and keyhole inclination angle under the changing welding parameters. In addition, a feedforward neural network (FNN) model was established to concern the optical features and geometrical parameters (keyhole and melt pool) and also a support vector machine (SVM) model was built to relate optical features and welded defects including blowout, humping and undercut [153]. Deriving from the the collected keyhole images, a sequential forward searching algorithm was combined with a random forest classifier to select ten penetration status features (PSFs). It is found that the weld penetration prediction model based on the PSFs has higher prediction performance in identifying the weld penetration status [63]. Recently, Fig.19 used the optical coherence tomography (OCT) to measure the capillary depth of the keyhole during deep penetration welding. An artificial neural network (ANN) approach could be utilized to reveal correlations between the weld depth signal and the weld seam surface quality, underlining the high level of information contained in the OCT signal about characteristic process phenomena that affect the weld seam quality [172].

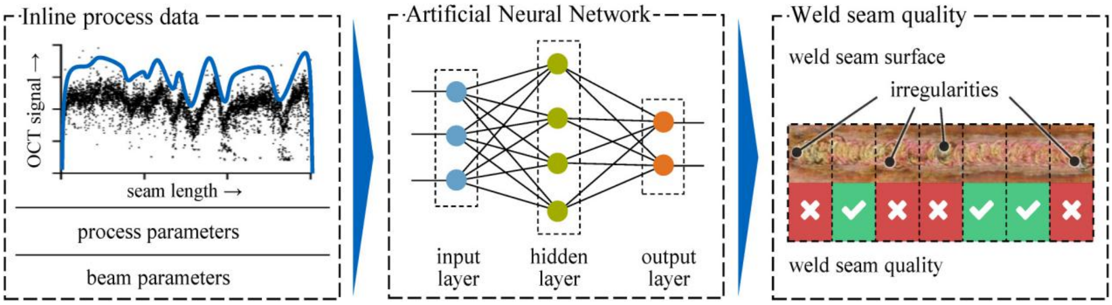

Fig. 19 Prediction of the weld quality based on OCT data and ANN model [172].

5.2 Modern deep learning method

As noted above, the classical machine learning method mainly integrate the process of feature extraction within the data-driven model to predict the weld quality and defects. However, the feature extraction methods through handcrafted processing algorithms often require much prior knowledge and are always specific to the task. In addition, the limited handcrafted features of melt pool with conventional image processing techniques may not be enough to describe the laser welding characteristics [178]. Consequently, it is necessary to design an efficient deep Learning (DL) approach to realize automatic feature learning and improve the weld quality. The deep learning models are capable of extracting more refined and complex characteristics, which providing higher classification accuracies than conventional approaches based on feature engineering and traditional classifiers. Therefore, more researchers have attempted to introduce deep learning to analyze the raw monitoring information deriving from the LBW process.

5.2.1 Convolutional neural network (CNN)

As a dominant DL architecture, the state-of-the-art convolutional neural network (CNN) exhibits brilliant abilities of high-level feature learning with the multiple levels of hierarchical non-linear information processing. More recently, the CNN model has gained increasing attention in the area of weld manufacturing field, which is employed to undertake many tasks including welding defects detection [173]-[176], penetration monitoring [177]-[181] and quality diagnosis [182]-[186].

For example, Günther et al. [128] suggested a deep learning scheme for extracting relevant features from in-process laser welding data. They used a deep learning-based auto-encoder with fully connected layers to create a new latent feature space of 16 features that describe the welding images. With the help of these features they used an SVM to predict the photodiode welding signal in the near feature based on image features. Higher prediction accuracies were achieved compared to an approach using PCA. In 2019, the work by Zhang et al. [176] presented a CNN-architecture that uses features extracted from image and photodiode signals recorded during laser welding to detect welding imperfections. The approach shows promising results compared to a traditional ANN model, although it was not used to extract features from raw sensor signals.

In addition, a typical CNN-based classification model was proposed for identifying the different welding defects (under penetration or burn-through) in pulsed GTAW with the three-way pool images, which demonstrates a better performance with a higher classification accuracy of 99.38 % [173]. The University of Kentucky[178]-[181] developed an end-to-end CNN approach to extract the visual features automatically from top-side GTAW pool images and predict the resultant penetration status. Gonzalez-Val et al. [186] presented ConvLBM, a novel approach to monitor laser-based manufacturing processes in real-time. The ConvLBM uses a CNN model to extract features and quality indicators from raw medium-wavelength infrared coaxial images. The results demonstrate the ability of ConvLBM to represent process dynamics and predict quality indicators in two scenarios: dilution estimation in laser metal deposition and location of defects in laser welding processes. Moreover,

Fig. 20 applied a deep CNN model to reveal the unique signatures of the wavelet spectrograms from the laser back-refection and acoustic-emission signals. The autonomous classification of the revealed signatures is tested on reallife data, and the confidence of the quality classification ranges between 71% and 99%, with a temporal resolution down to 2ms [182].

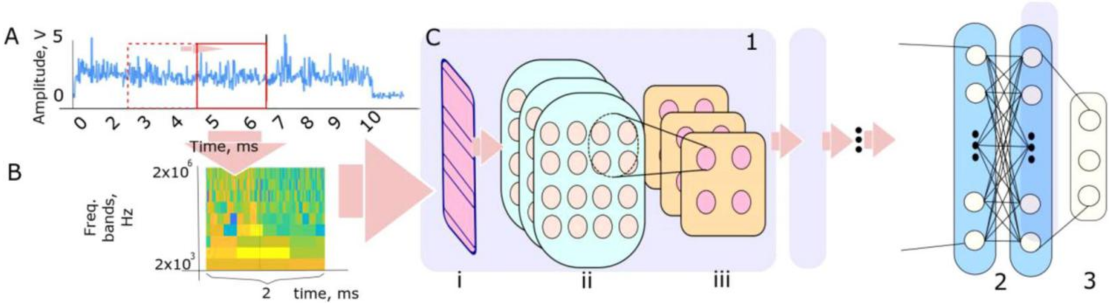

Fig. 20 Supervised deep learning for realtime quality monitoring of laser welding [182].

5.2.2 Ensemble deep learning method

Considering the laser welding process is quite dynamic along with the plume and spatter orientation vibration driven by the melt pool variation, the proposed CNN architecture can only deal with the static information in the images/signals. Therefore, using the standard CNN architecture may be not accurate enough for high-precision defect identification during high dynamic laser welding process. To deal with the issue above, a hybrid convolutional neural networks (CNNs) was proposed for powder-bed fusion (PBF) process monitoring [187]. The hybrid models can learn both the spatial and temporal representative features from the raw images automatically, which demonstrates the superior performance of the proposed method compared with the traditional methods with handcrafted features. Also, a hybrid network model namely CNN and LSTM (long short-term memory) was developed to learn/extract the nonlinear features of time series signals [196]. The CNN-LSTM ensemble method can fuse the multi-sensor information of dynamic welding process and implement the prediction of welding quality characteristics during pulsed GTAW process of aluminum alloy including normal penetration, lack of fusion, sag depression, burn through and misalignment.

In addition, Knaak et al. [188]-[189]developed a novel ensemble deep learning architecture based on CNN-GRU (gated recurrent units), which uses spatio-temporal features extracted from infrared image sequences to locate critical laser welding defects including lack of fusion, sagging and weld deviation. The proposed method is finally validated on previously unknown welding trials, achieving the highest detection rates and the most robust weld defect recognition accuracy. In order to improve the feasibility and generalisation ability of CNN-based laser welding penetration recognition method, a label semantic attention (LSA) mechanism was designed to guide CNN to learn the discriminative visual features in the raw melt pool images [197]. The proposed knowledge-data hybrid driven method has not only fast convergence speed and high accuracy, but also low dependence on model complexity and data size. Moreover, it does not add too many parameters and test time, and can meet the industrial needs in real-time monitoring the laser welding process.

To sum up, it should be noted that processing this data can require significant computational power and thus there may be a need to filter the available input data for these ML algorithms to be successfully deployed for real-time applications. Furthermore, the volume and complexity of process factors and responses in laser welding process may result in a large volume of coincidental correlations, making the identification of causal relationships difficult by using ML solely. Despite this, the ML algorithms especially for deep learning may be useful in identifying the correlations and developing the process maps which are needed for real-time process control, especially when conventional analytical approaches are insufficient.

6. Major challenges and potential solutions

Generally, the main object of in-situ monitoring is the improvement of reproducibility and assurance of process reliability/quality during metal-based LBW manufacturing. However, welding quality assurance is not the only aspect concerning monitoring of laser manufacturing process, and the other significant uses for in-situ monitoring is observing, experimenting, gathering of information and understanding the process and related laser phenomena, and finally developing adaptability of the process. Despite significant progress made in optical monitoring of the LBW process, there are still many challenges towards applying these sensing approaches and predicting the welding quality in industry, which as follows:

1) Physical realizability of multi-sensor fusion

The first challenge is to develop the in-situ sensing ability to capture the abundant and valuable information of the laser physical phenomenon with sufficient precision. During LBW process, strong brightness and high temperature of metal plume and spatters increase the difficulty to clearly observe the laser interaction zone. Moreover, the dynamic process involves a series of consequent phenomena including melt pool, keyhole, plume and metal spatters, which carries various types of welding information that directly determining the final welding quality. One single sensor or system may be not sufficient to describe the complete and complex welding process. As such, it has a rather low detection precision and can only identity a few kinds of welding defects. Thus, more investigation needs to be geared toward in-situ monitoring of LBW process by means of multiple sensors such as multi-wave optical radiation, acoustic, thermal and visual signals. Very few efforts such as refs. [90],[93]-[94] have designed a multi-sensor monitoring and analysis platform to gain overall knowledge of the welding process, the scope and depth regarding multi-information fusion technology is still limited and thorough study is needed.

When two or more sensors are applied with different acquisition resolutions, data fusion techniques are urgently needed to combine the large-scale data and to match the co-ordinate systems of the sensors, and further developments in identifying multiple laser welding events within a single framework is required [198]. To make full use of all the available information, it is promising to utilize the intelligent sampling and compressed sensing techniques [199]. In addition, unified fusion theory and data fusion architecture need to be developed for implementing large-scale data mining in a statistical-analysis framework. It is believed that sensor fusion system in conjunction with latest advance in artificial intelligence techniques would play an important role in laser welding monitoring and quality inspection.

2) Accurate characterization of melt pool behavior

The application of multiple sensors has provided large amount of original data (signals/images) for laser welding monitoring. In order to quantitatively characterize the laser physical phenomenon, it is necessary to extract the key measurement characteristics (*KMCs*) by means of the advanced image/signal processing algorithms. Unfortunately, the very high sampling frequency for process monitoring, together with the large dimensionality of the obtained data makes real-time feature extraction a challenging task that motivates the research of novel and computationally efficient techniques.

- For image processing field, the feature extraction in laser welding applications is generally performed using geometric or statistical information about the detected keyhole, melt pool or plume. Although it is possible to obtain the abundant visual features (i.e., shape, dimension or textural information) with image processing algorithms and select relevant features by automatic feature selection [127], it is still a great challenge to determine the most essential features for characterizing the complicated dynamic process. Moreover, it is also difficult to adaptively extract the distinctive features of the highly dynamic melt pool/keyhole with common image processing algorithms [129]. One potential solution to the image processing challenge is the combination of the low-level handcrafted features (based on prior knowledge) and high-level discriminative features (deep learning model) [200], which could comprehensively characterize the behaviors of melt pool and plume during LBW process;
- For signal processing field, the optical radiation signals from the photodiodes, spectrometer, pyrometer etc. carry valuable information about the LBW process. It is possible to develop many signal analysis methods (fast Fourier transform, power spectrum) to find out the relationship between emission characteristics and weld quality characteristics, in order to evaluate laser process quality. However, these methods are based on the assumption of stationarity and linearity of the detected signals. Unfortunately, the laser welding defects by their nature are time-localized transient events. To deal with non-stationary and nonlinear time series signals, one potential solution to the signal processing is to develop some advanced time-frequency analysis techniques such as the Short-Time Fourier Transform (STFT) [148], Wavelet Transform (WT) [147], Wigner-Ville distribution (WVD) [150], in order to interpret and visualize the key information about the weld quality. In addition, the optical measurement techniques could not detect microstructural defects, such as porosity or cracks formed within the metal materials, since these types of defects are hardly detectable by the only use of the optical sensors. Therefore, additional detection techniques (i.e., acoustic emission [201]-[202]) as well as the fusion sensing will be the next challenge for the authors to investigate.

3) Reliability and generalizability of machine learning-based model

Due to the extreme complexity of the laser-material interaction, it is very difficult to build a suitable physical model for real-time quality diagnosis and process control. Under such circumstances, the machine learning (ML) methodology allows developing the data-driven models rather than complex physical ones. The major challenge in the development of ML algorithms is to establish an accurate internal relationship between the welding parameters, process characteristics and the actual quality. The challenges associated with data-driven in-process monitoring techniques are: (i) not directly observe the welding defects/appearance but acquire intermediate signals correlating to the corresponding quality, (ii) the interpretability and feature-learning ability of the ML model need to be clearly elucidated, especially for the deep learning model (i.e., convolutional neural network), which is usually considered as a black box [200]; iii) the training samples shortage should be taken into account. In actual welding environment, obtaining a large amount of effective samples, especially the defect samples often requires time-consuming and expends great cost. Moreover, the samples shortage problem not only affects the model predicting performance, but also weakens the model generalizability considering that there would be more data under other welding conditions that have not been discovered yet [173].

An alternative solution for meet these challenges is the full integration of physics-driven (process mechanism) and data-driven (machine learning) models, which is becoming the latest trends and research focus of the intelligent welding field [204]. Combining both approaches will allow the physics-driven approaches to support the interpretability of results deriving from data-driven techniques, revealing the hidden contents of the so-called “black-box”. Meantime, the outputs from the physics-driven models applied as inputs to the data-driven models may provide a larger set of input data for training, which could further increase the reliability and generalizability performances of the ML methods in predicting and controlling the welding quality.

7. Conclusions

There is a rapidly increasing number of studies in the literature aimed at understanding the nature and process of LBW, their effects on the product quality and how they can be mitigated or avoided by acting on several controllable parameters. Indeed, the lack of robustness and stability of metal LBW processes has been widely pointed out as one major issue that deserves considerable research efforts and technological advances. The development and implementation of in-situ monitoring solution represents a priority to push forward the industrial breakthrough of LBW systems. This review summarized some conclusions as follows:

1) In-situ sensing has been proposed for different observable signatures, including the melt pool, plasma plume and spatters. Other in situ non destructive inspection systems are currently under development, e.g., optical coherence tomography, X-ray and may be implemented and tested in the near future;

2) Based on the optical radiation and visual sensing technology, extensive advanced image/signal processing algorithms have been widely applied to extract the

key feature and describe the significant characteristics of the laser physical phenomenon;

3) Recent development led to advanced process monitoring systems which integrate the machine learning techniques for weld formation prediction and defect diagnosis, in order to control the weld quality. More researchers started to introduce deep learning to analyze the raw information and extracting complex characteristics of the laser welding process;

While these are all areas currently under investigation, there remains significant scope for the development of new process monitoring approaches. As this field matures further, we will no doubt see combination of in-situ sensing approaches being developed and further advances towards characterization and process model. Each development shows promise to increase reliability and stability for LBW processes, thus unlocking the full potential of intelligent and sustainable manufacturing technologies in various industry fields.

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Declaration of competing interests

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.

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