Chapter

Online Measurements in Welding Processes

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Abstract

The online measurement of principal magnitudes in welding processes is important to close the control loop and meet the project requirements. But, it is difficult because of the adverse environmental conditions that exist near the weld pool. Some conventional measurement techniques are used, but under these conditions, indirect sensing techniques are a better option. Sensor fusion algorithms and indirect sensing techniques allow estimate magnitudes that are impossible to measure directly. Sensor fusion is used to describe the static and dynamic behavior of process variables and is based on several areas of knowledge, such as statistics and artificial intelligence. By combining different sensing technologies to take advantage of each one, it is possible to obtain better sensing results. In this chapter selected sensing techniques and estimation algorithms used online for collecting values on the welding process are shown. Special attention is given to sensor fusion techniques. Some real applications and innovative research results are discussed.

Keywords: estimation, online measurement, sensor fusion, welding

1. Introduction

The welding process is used by many manufacture companies in a wider range of applications. Many studies have been carried out to improve the quality and to reduce the cost of welded components. Part of the overheads is employed in the final inspection, which begins with a visual inspection, followed by destructive and nondestructive testing techniques. In addition to cost raises, a final inspection is conducted when the part is finished only. When a defect occurs during welding, it can be reflected in the physical phenomena involved: magnetic field, electric field, temperature, sound pressure, radiation emission, and others. Thus, if a sensor monitors one of these phenomena, it is possible to build a system to monitor weld parameters and quality.

For years, much has been done to predict problems in welding to make it a stable process capable of making union parts with minimal human interference. Despite various sensors used in welding processes, there is still no effective option able to identify, directly, the weld bead characteristics obtained during the process. This is a limiting factor in the process control because weld bead characteristics can only be determined after the completion of welding through testing (destructive or not) when no control action can be taken.

In the last decade, measurements of multiple sensors are used to estimate some geometric parameters of the weld bead, such as the weld penetration, reinforcement, and width, and to classify the process stability. These estimations can be made online[1] and can be used to control the weld bead geometry formation. More recently, research has shown the possibility of estimating some microstructural characteristics and thermally affected zone dimensions, as shown in [1]. These estimations can be used to limit the control actions so as not to affect the desired characteristics of the weld bead. These techniques do not eliminate destructive testing but greatly reduce its use and prevent the defect formation or loss of characteristics.

In the welding processes, many variables can be used to control the geometry and quality of the final product. For this, other variables need to be measured or estimated. Some variables can be measured or modified online, directly in the welding power source, such as welding voltage and welding electric current intensity. Others can be measured using noncontact sensing methods, such as width and reinforcement of weld bead, drop volume, and electrical stick-out. But several variables, necessary to close the control loops, are difficult to measure online. This difficulty is due to the extreme conditions in the arc zone, because the electric arc is a powerful radiation emitter, in a long range of the frequency spectrum, including high temperature and visible light, generating steam and droplets of molten metal, coming from the electrode and the base metal. For these latter cases are necessary estimation methods based on models of welding processes that may include the power source and the robotic system used to move the torch or piece.

For the automation and control of complex manufacturing systems, a great deal of progress came up in the last decade, for precision and online documentation (bases for the quality control). With the advent of electrically driven mechanical manipulators and later the whole, relatively new, multidisciplinary mechatronics engineering, the need for information acquisition has increased. The acquisition is, in many cases, distributed through the system, with strong interaction between the robot and its environment. The design objective is to attain flexible and lean production. The requirement of real-time processing of data from multi-sensor systems with robustness, in an industrial environment, shows the need for new concepts on system integration.

Technology advancements seek to meet the demands for quality and performance through product improvements and cost reductions. An important area of research is the optimization of applications related to welding and the resultant cost reduction. The use of nondestructive tests and defect repair are slow processes. To avoid this, online monitoring and control of the welding process can favor the correction and reduction of defects before the solidification of the melted/fused metal, reducing the production time and cost [2].

Developments in microelectronics have led to rapid advances in welding power sources. With the use of fast microelectronic circuits, the speed of welding process control and welding parameter adjustment has been increased tremendously, and dynamic control over the arc and molten metal transfer have become possible. Research and development carried out by manufacturers of welding power sources focus on rapid optimal control of the welding parameters during welding. Modern welding sources are equipped with special control functions of arc and molten metal transfer, focusing on two basic areas: The first area of focus is on welding thin metal sheets (0.53 mm), and the second is on high-productivity thick metal sheet welding (over 5 mm) [3].

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[1] When the measurement or control action is made inside the process flow and during the process execution, this task is classified as online. When the measurement or control action is made outside the process flow and before or after the process execution, this task is classified as offline.

With continuing advancements in digital and sensor technology, new methods with relatively high accuracy and quick response time for the identification of perturbations during the welding process have become possible. Arc position, part placement variations, surface contaminations, and joint penetration are key variables that must be controlled to ensure satisfactory weld production [4]. The techniques related to welding process optimization are based on experimental methodologies. These techniques are strongly related to experimental tests and seek to establish relations between the welding parameters and welding bead geometry.

Researches related to adaptive systems for welding seek the improvement of welding bead geometry with direct (if based on monitoring sensors) or indirect monitoring techniques. The indirect monitoring systems are the more used, looking to link elements such as welding pool vibrations, superficial temperature distribution, and acoustic emissions to size, geometry, or welding pool depth [5]. The most used approaches in welding control are infrared monitoring, acoustic monitoring, welding pool vibrations, and welding pool depression monitoring as shown in [6]. The literature analysis made in [7] shows a similar conclusion, but adds vision techniques with the same level of use with infrared measurement.

The majority of modeling methods used in the past were based on the physics and chemical characteristics of the process components. This method needs great knowledge about welding processes, and, because of its complexity, these magnitudes are difficult to obtain and keep constant throughout the process, causing inaccuracies in the models. With the development of information processing capabilities, black box modeling methods were successfully used, as such the statistics and probabilities, but needs very complex models because of the nonlinearity of the welding process and the correlation between variables. Nowadays, the black box methods based on intelligent artificial algorithms are predominant as shown in [7], where 29% of models analyzed were obtained using intelligent artificial algorithms, 18% used image processing (which can include intelligent artificial algorithms such as deep learning methods), 12% used statistical methods, and only 2% used physics and chemical characteristics. Also, recently, big data and data mining algorithms are to be introduced in industrial applications.

This chapter focuses on the online measurement of main magnitudes in welding processes to close the control loop and allow the welding power source and robot parameters to be adjusted. These actions make it easier to meet the project requirements, reduce the cost of welding production, and increase productivity by reducing the number of parts rejected in final quality inspection. The next sections discuss the sensing and analysis techniques used to measure or estimate important variables in welding processes, with emphasis on the conventional gas metal arc welding (GMAW) process. A summary of its evolution is also shown, and some examples of algorithms to measure data processing are discussed.

Also, a novel modeling method, based on a sensor fusion algorithm, is shown. This method uses dynamic information of welding processes to improve the model response, rather than relying on static models used in research found in the literature. The method uses arc welding measurements and thermographic information to estimate the weld bead penetration. The algorithm obtains the thermographic features and supplies information about the amount and spatial distribution of the energy in the workpiece, minimizing the errors when multiple inflection points are found because it does not use the second derivative for the calculation of thermographic width. Besides, volume calculations are performed using the actual thermographic curve instead of the ideal Gaussian curve used in most research as an approximation value and using more complex equations. This approach uses only addition operations, simplifies calculations, and improves model accuracy, allowing its implementation in an embedded device. The actual application area is automatic control, arc welding, and sensor fusion research.

2. Measurements in welding processes

Automatic welding is affected by disturbances in the production parameters and welding conditions. Variations in components' position and dimensions, weld joint misalignment, oil in the surface and other improprieties in materials, instability in welding wire speed, and shielding gas flow are examples of disturbances. However, by adding measuring systems, the control system may have a better performance when disturbances are found. For this purpose, the disturbances and affected variables must be measured or estimated online, to counteract the effects of the disturbances through the control actions. These variables can be different in each process type or change your significance in the process. Some variables can be measured directly from the welding power source or using indirect measuring techniques, and others need to be estimated from measured variables. This last group includes the weld bead depth or penetration.

In welding processes, the variables can be classified depending on whether they can be measured or modified and if these actions can be done online or offline. Responding to this classification, the variables in welding processes can be divided into five basic groups [8]:

- Fixed, which cannot be modified by the operator but defined in the process design
- Adjustable online, which can be modified during the process
- Adjustable offline, which can be modified only before starting the process
- Quantifiable online, which is measurable during the process
- Quantifiable offline, which is measurable only after the process ended

An example of variables and groups for the constant voltage GMAW orbital process is shown in **Figure 1**, and some measurement techniques are described in the following sections.

2.1 Measurement of welding variables

The most common measurement variables in welding are related to the power supplied to the process by the unit of material length or area, and most are defined or measured by the power source. In conventional arc welding processes, these variables are *electric voltage*, *intensity of electric current* (also called simply *amperage* or *welding current*), and *wire feed speed* in processes with material addition. The parameters to control the waveform of voltage or electric current in the advanced arc welding process are important also. Other variables can be necessary to define and know, as *gas flow*, *pre-gas time* and *post-gas time*, *source impedance*, and time or position when the arc is open and closed (*arc status*). In laser welding processes, *laser power*, *pulse rate*, *focal distance*, and *spot size* are important too.

The modern welding power sources have one or various microcontrollers or microprocessors to control source operations, data acquisition, and

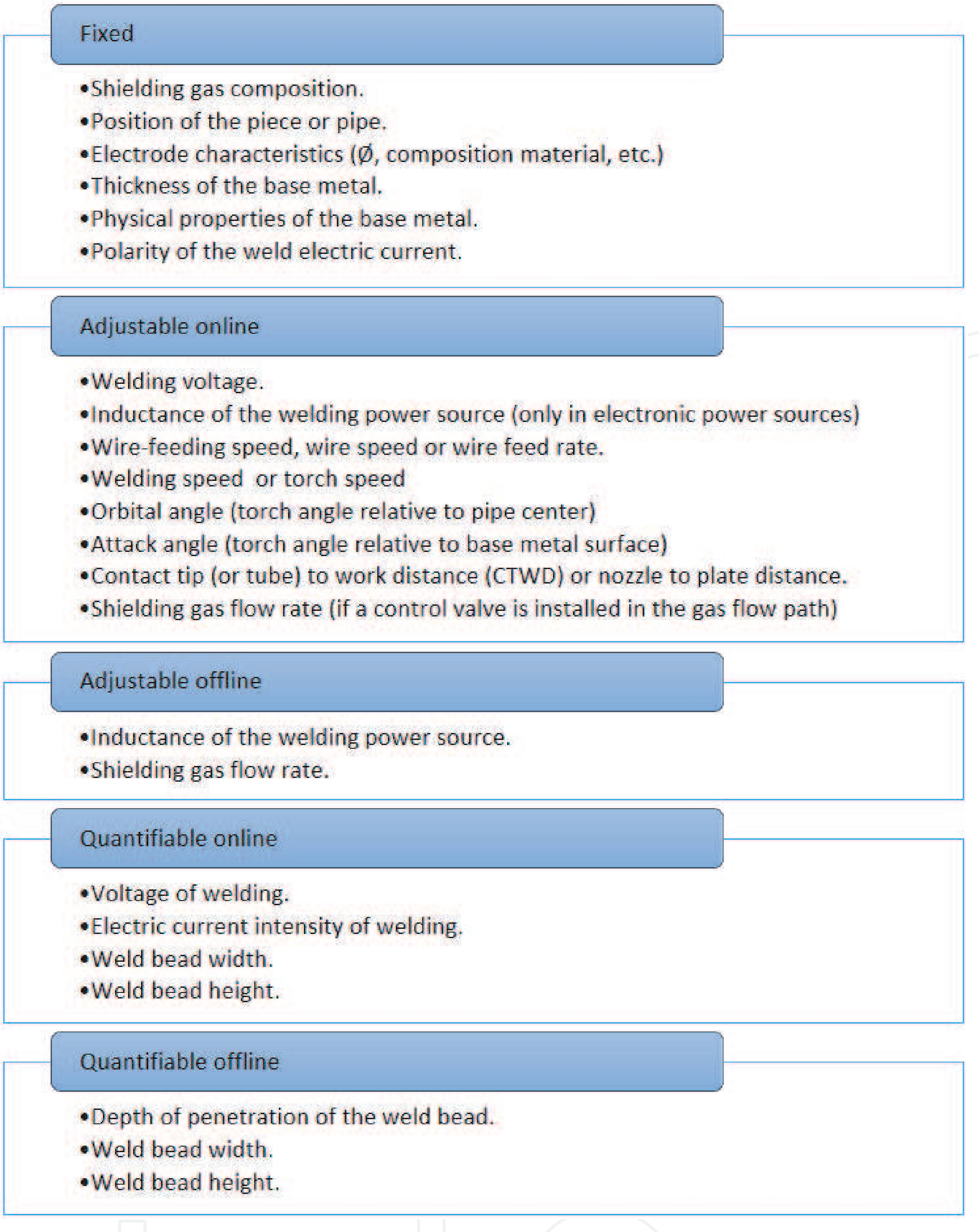

Figure 1.
Variables and classification groups to conventional constant voltage gas metal arc welding (GMAW) process (adapted from [8]).

communications. The communication interface usually implements a serial protocol or digital and analogical inputs and outputs to obtain or send information from an external supervisory control system (computer, programmable logic controller, and robotic system, among others). This interface can be used to synchronize work between power sources and robotic systems, other machines, control levels, or factory management. The welding variables, as voltage, electric current, and wire feed speed, can be measured and modified using this interface. Some commonly used standard network protocols are RS-232, RS-485, Modbus (RTU, TCP, or UDP), CAN Bus, DeviceNet, Field Bus, and Ethernet. Other companies define their protocol such as the Arclink developed by Lincoln Electric and SpeedNet by Fronius.

The communication protocol can be “open” or “proprietary.” In the first case, the user can communicate his control system directly with the power source using the communication protocol description. In the second case, he needs to buy and use proprietary software or hardware. The implementation of protocols used in

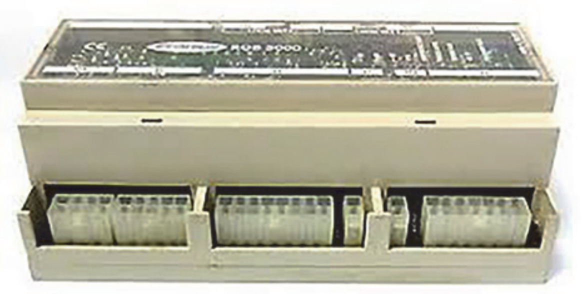

Figure 2.
Fronius interface to translate the information between serial protocol and data acquisition system with digital and analogical inputs and outputs.

modern power sources is serial[2], and information is obtained or sent in digital format.

The old welding power sources can have an interface with digital and analogical inputs and outputs, to let the monitoring and control of the source. These power sources need a dedicated data acquisition and control system to convert the analog values in digital information and vice versa. The user, using this system, can monitor and control the power source operation partially or fully. To design or select the system, the sampling time, resolution and range of analogical inputs and outputs, and range and type of digital inputs and outputs, based on the power source characteristics and application requirements, should be considered.

Some manufacturers offer hardware interfaces to translate the information from serial protocol to digital and analogical inputs and outputs. If you do not have conditions to use a serial protocol, these interfaces can help to get and send information to power sources. These systems can be more slow, inaccurate, and inefficient than serial protocol, because of the sequential conversions from analogical to digital (on the source), from digital to analogical (on the interface), and from analogical to digital again (on the acquisition system). The ROB 5000 of Fronius, shown in **Figure 2**, is an example [9].

2.2 Measurement of welding speed, welding angles, and orbital angle

Other variables that must be measured to control robotic welding processes are those that characterize the relative movement and position between the piece and torch. These variables can be obtained from the position control system of the robot, but many times an initial or absolute reference is necessary.

The relative movement between the piece and torch is defined by the *welding speed*. Sometimes, the torch is coupled to the robot manipulator and moves while the piece is fixed. Other systems fixed the torch and move the piece. More complex robotic systems move the torch and piece. In all cases, it is important to consider the relative speed between the torch and the piece to obtain the welding speed. This speed can be calculated using the torch and the piece speed obtained from the robotic system. On plane welding, the speed can be expressed in longitude per time unit, such as mm/s.

In orbital welding, the *orbital angle* is used to indicate the torch position in the polar coordinate system with the origin on the pipe axis. This measurement is very important because the welding conditions can be different for each orbital position. Its value must be obtained from the robotic system too. In this case, it is possible to express the welding speed using orbital angle per time unit, such as $^o/s$.

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[2] The information bits are sent one by one through a communication channel.

The *forehand angle* or *attack angle* is the torch angle side view relative to the base metal surface, which is the angle in direction of torch travel. The *work angle* is defined by the torch angle end view relative to the base metal surface as shown in **Figure 3**. These angles can be fixed before starting the welding and staying constant or can be controlled by the robotic system. In the second case, the angles can be calculated or obtained from the robotic system also.

2.3 Measurement of contact tip-to-work distance

The *contact tip-to-work distance (CTWD)* can be obtained from the robot control system related to torch or piece position, or it can be measured with a laser distance sensor. Other variables, such as *electrical stick-out* or *electrode extension* and *arc length* (see **Figure 4**) need more complex procedures to obtain a measurement because they depend on the fusion rate. All these variables are expressed in longitude unit, such as *mm*.

The first method to obtain the *CTWD* is more economical but has low accuracy. The zero references of the robotic system are calibrated with the workpiece position, but the surface variations and thickness of the material can affect the accuracy of the value. In arc welding processes, small variations in CTWD can affect the electric resistance of the arc, and consequently, the welding current and the heat input can be significantly affected. For example, reduction of the arc length causes

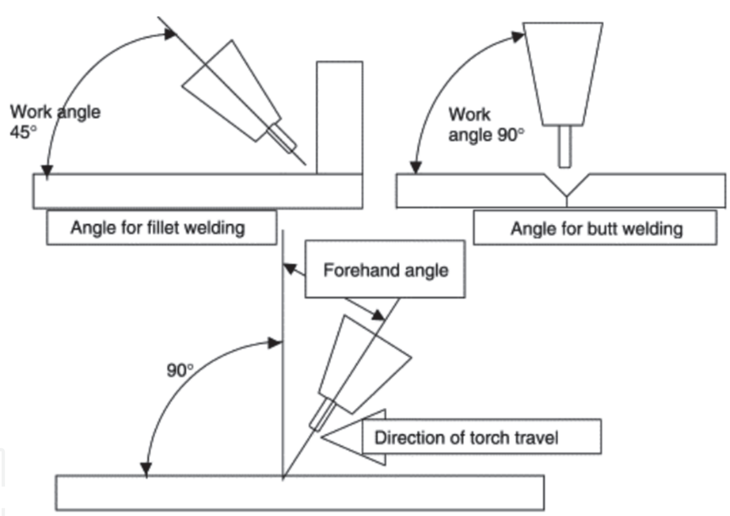

Figure 3.
Welding speed, torch angles, and orbital angle (adapted from [10]).

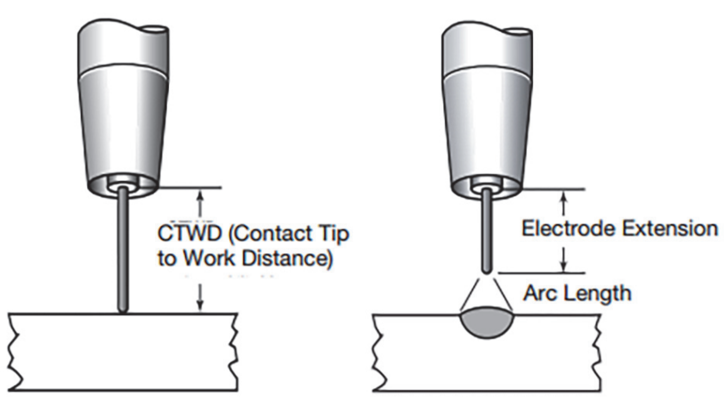

Figure 4.
Contact tip-to-work distance and electrical stick-out (or electrode extension) differences (adapted from [11]).

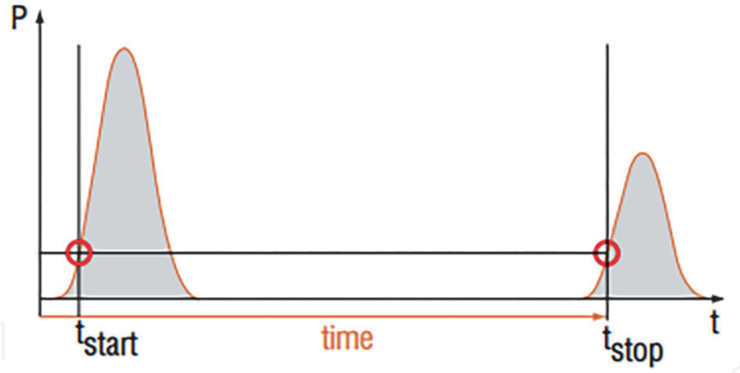

Figure 5.
Time of flight measurement principle (adapted from [12]).

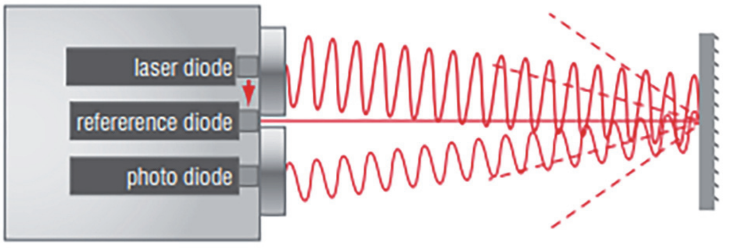

Figure 6.
Phase comparison measuring principle (adapted from [12]).

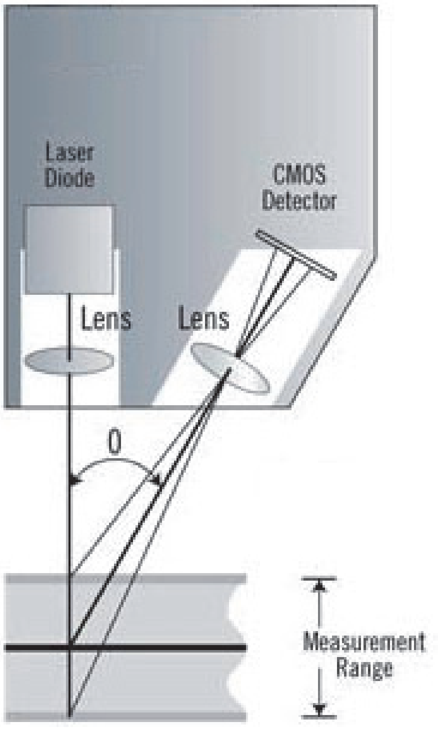

Figure 7.
Triangulation measuring principle (adapted from [13]).

the increase of heat input (and more current because it reduces the equivalent resistance of arc) which makes the wire electrode melt more quickly and thereby restore the original arc length.

A laser sensor can be more accurate, but the measurement point needs to be selected correctly. This sensor measures the distance to a point on the surface of the base metal of the piece, and it has three basic principles of operation: time of flight, phase comparison, or triangulation method.

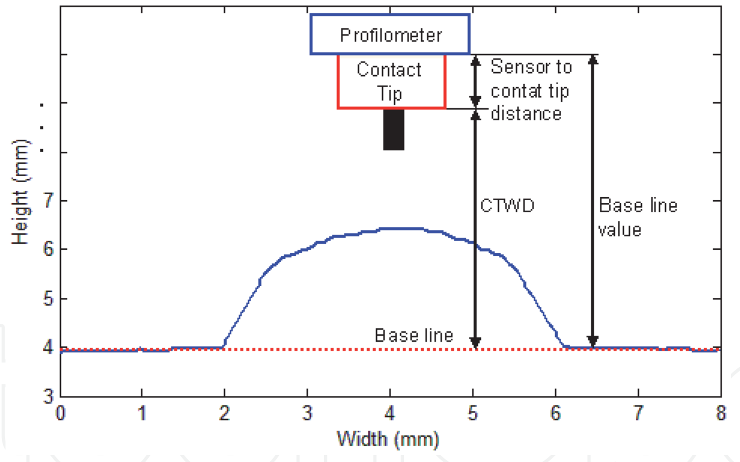

Figure 8.
Contact tip-to-work distance measurement [8].

In the time of flight measurement principle, shown in **Figure 5**, a laser diode produces short pulses which are projected onto the target. The light reflected from the target is recorded by the sensor element. The time of flight of the light pulse to the target and back determines the measured distance. The integrated electronics in the sensor compute the distance using the time of flight. Sensors using this principle are not sensitive to external light.

In the phase comparison measuring principle, a high-frequency modulated laser light with low amplitude is transmitted to the target as shown in **Figure 6**. Depending on the distance of the object, it changes the phase relationship between transmitted and received signals. Sensors using this principle operate with high accuracy for measurement distances up to 150 m.

In the triangulation method, shown in **Figure 7**, the laser beam is projected and reflected from a target surface to a collection lens. The lens focuses an image of the spot on a linear array camera. The camera views the measurement range from an angle at the center of the measurement range. The position of the spot image on the pixels of the camera is then processed to determine the distance to the target. The camera integrates the light falling on it, so long exposure times allow greater sensitivity to weak reflections.

The most used laser emitter distance sensors are in the wavelengths of red color (close to 658 *nm*), but in recent years, blue-violet lasers with a shorter wavelength than a red laser (close to 405 *nm*) have been used in welding processes and others that work with red-hot glowing metals. This shorter wavelength provides higher optical resolution and noise reduction. The blue-violet laser sensors enable more reliable measurements on these processes than red laser sensors.

Other research methods use the voltage and current feedback signals from the welding process, computing the minimum resistance during the short circuit period, and uses this value to estimate the *CTWD* after applying a correction factor for the duration of the short circuit. The effect of wire feed speed, actual CTWD, and shielding gas on the correction factor is determined experimentally [14].

The *CTWD* can be calculated with the same bead profile obtained from the laser profilometer. The distance between the torch contact tip and the sensor reference is fixed and known. The CTWD is the difference between the baseline value and this distance, as shown in **Figure 8**.

2.4 Measurement of welding joint and weld bead geometry

The quality of arc welding is commonly described by the geometry of the molten weld pool and the weld bead because the mechanical properties of the welding joint are reflected in these geometry characteristics. The geometry of the weld bead is a set of parameters defined in the design stage, and to achieve the required quality, it should be measured and controlled throughout the process. The parameters or variables which define the most important characteristics of the geometry of the weld bead (including the weld pool) are the *weld bead width*, the *weld bead reinforcement*, and *weld bead depth* or *weld bead penetration*, as shown in **Figure 9**.

The visual information of the molten weld pool is used by expert operators to control the welding process in manual welding. In automatic welding processes, this information can be used to improve the control behavior and achieve the desired quality in the welding joint. In arc welding processes, the geometry parameters are governed by many factors, such as *welding current*, *welding voltage*, *wire feed speed*, *welding speed*, and the *contact tip-to-work distance*. Then, for successful control of geometric variables, it is necessary to provide feedback to the control system.

For feedback implementation, it is important to know that the process' adverse environmental conditions, in the vicinity of the electric arc and the molten pool,

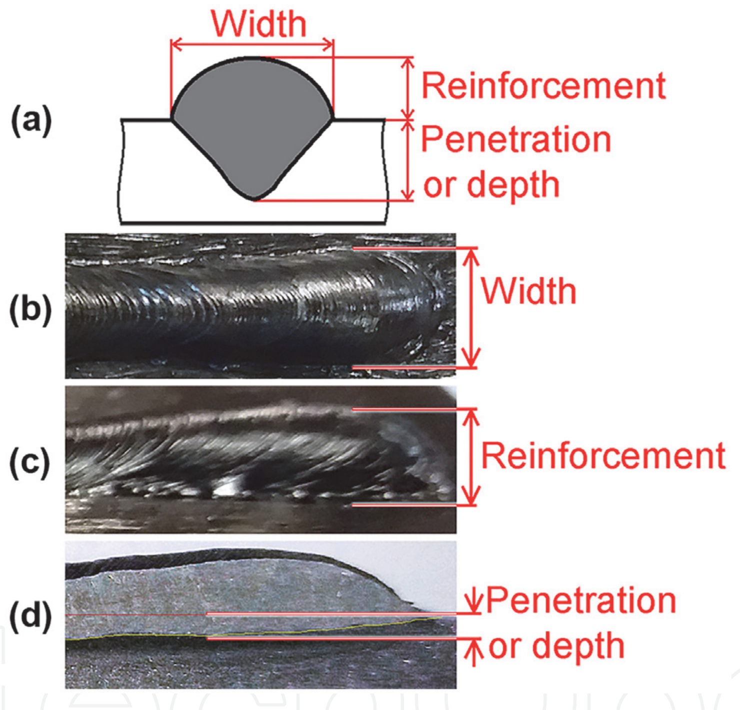

Figure 9.
Geometric dimensions of the weld bead: (a) cross-section, (b) top view, (c) side view, and (d) side view of a longitudinal cut [7].

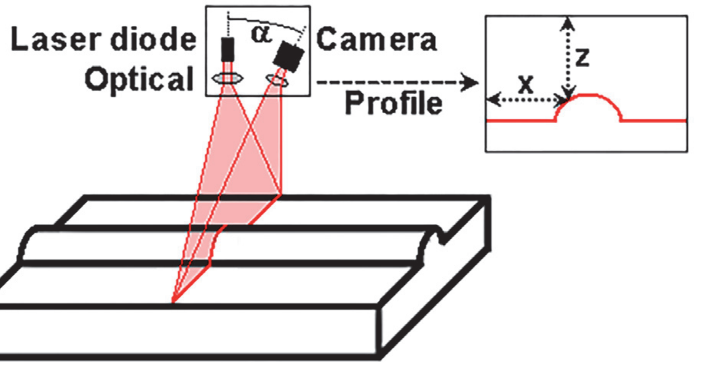

Figure 10.
Two-dimensional laser triangulation principle [7].

would damage the measuring instruments that require physical contact with the surface of the piece. These conditions make the measuring of the weld bead geometry a difficult task using conventional measuring principles. Instead, noncontact techniques have been developed and employed successfully.

For this purpose, vision sensing is a promising solution. One common method is formed by a laser beam, which draws one or more lines on the surface to be measured, the image is filtered to obtain only the wavelength emitted by the laser, and a camera or matrix image sensor captures the line created by the laser. Subsequently, using image processing algorithms and triangulation techniques, a profile of the piece with the required information is obtained.

This system, referred to as a laser scanner or profile sensor, is shown in **Figure 10**. In it, the optical system projects the diffusely reflected light of this laser line onto a highly sensitive sensor matrix. From this matrix image and the angle between the camera and the laser diode (α), the controller calculates the distance information (z-axis) and the position alongside the laser line (x-axis). These measured values are then projected in a two-dimensional coordinate system that is fixed for the sensor. To obtain three-dimensional measurement values, the sensor or workpiece can be moved in a controlled manner.

Another way to obtain a three-dimensional profile is by using a laser pattern with a dot matrix or line grill, as shown in **Figure 11**. The two-dimensional information is processed using triangulation techniques to obtain a three-dimensional profile. In [15], the weld pool surface deformation is obtained from the projection pattern using the deformation of the lines (see **Figure 11b**) or the distance between points (see **Figure 11c**). Other implementations of this method are shown in

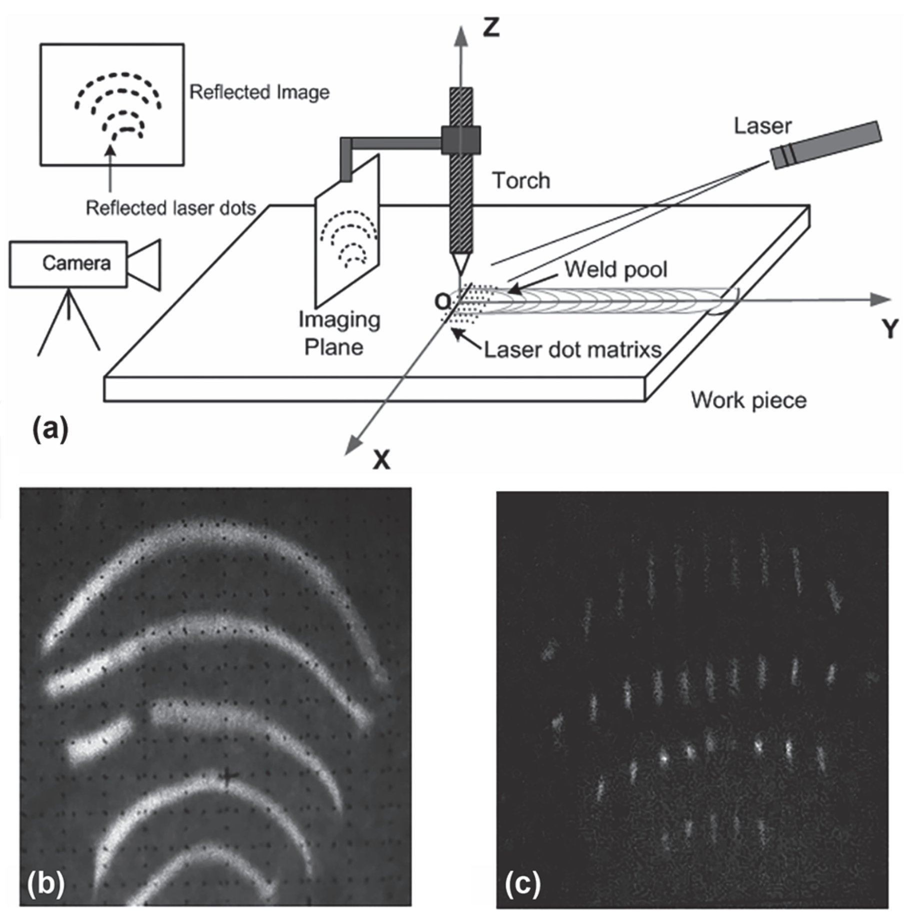

Figure 11.
Three-dimensional profile of the weld pool surface using structured light and triangulation method: (a) diagram of measure system, (b) reflected image using line laser pattern, and (c) reflected image using dot laser matrix (adapted from [15]).

[16–18]. In these methods, the uncertainty to recognize the real position is a problem. For this reason, a point of the pattern dot is intentionally missed to serve as a reference.

It can also use the same measuring principle to obtain a profile of the weld joint before joining the one. This allows the implementation of algorithms to define or adjust the trajectory to be followed by the torch (seam-tracking algorithms). Similarly, it is possible to estimate the amount of material required (deposition rate) for the formation of a bead with the desired dimensions [7].

The use of video cameras to measure the weld bead width and reinforcement is possible too, as is shown in [19–21], but these methods need optimal light conditions and are difficult to apply in the industrial environment.

These principles cannot be applied to penetration measurement, and this variable could be estimated from a different way. Due to the complexity of the measurement methods, we are going to dedicate another section to show some estimation methods of this magnitude.

2.5 Measurement of weld bead depth or penetration

Total penetration in welding processes is important to ensure weld quality. When the total penetration takes place, the melt weld pool crosses to the bottom side of the workpiece, as shown in **Figure 12**. The depth of penetration of the weld bead can be determined by nondestructive testing techniques such as ultrasound or X-ray. However, the portability and robustness of these traditional instruments are not a good option for the harsh conditions of the process and to develop an online measuring system. Because of that, many research works attempt to detect total or

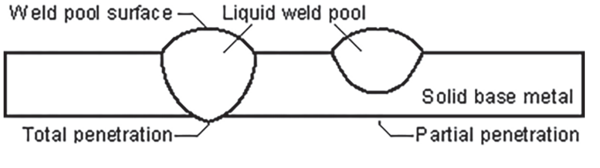

Figure 12.
Total and partial penetration in the weld bead [7].

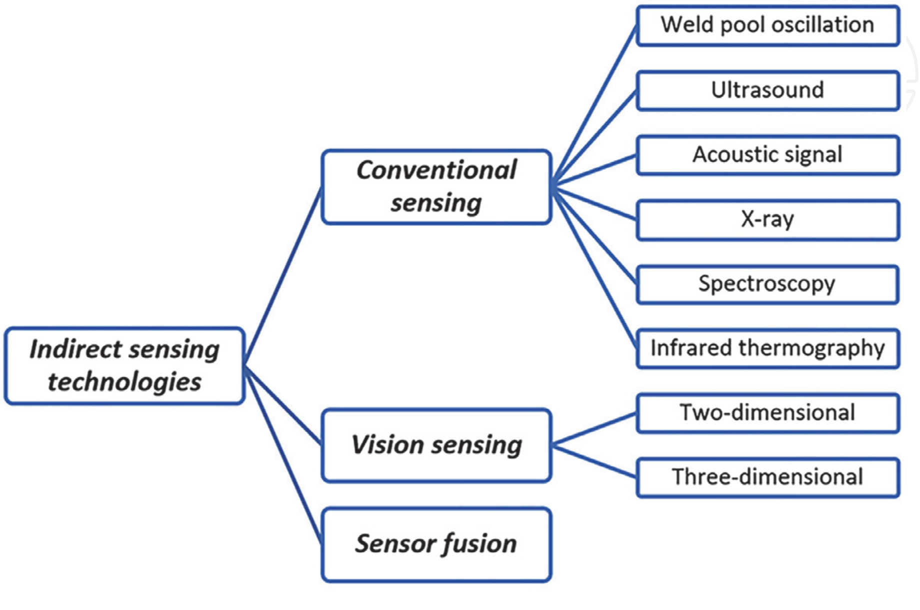

Figure 13.
Indirect sensing technologies used to monitor the bead and weld pool [7].

partial penetration with other methods, but few obtain a useful value for the control system algorithm.

Measurement of the backside width of the weld pool can be used to ensure total penetration, but this method is difficult because of the reduced space, limited movements, and restricted access, among other conditions, that make it impossible to place the sensors under the weld pool.

The front side of the weld pool offers information about the total penetration status. This information includes the *temperature of arc and weld pool*, *arc voltage*, *arc light*, *arc sound*, *geometry parameters*, *oscillation frequency*, and *resonance frequency*, among others. For obtaining this information, indirect sensing technologies are used. These measuring technologies can be classified as conventional, vision, and multi-sensor or sensor fusion technologies, as shown in **Figure 13**.

Conventional sensing technologies monitor parameters closely related to the weld bead and the weld pool geometry. It includes ultrasound, infrared thermography, weld pool oscillation, arc sound, and X-ray, among others. Vision sensing technologies obtain these features as skilled welders do. It can be divided into two-dimensional and three-dimensional sensing. These methods are applied to obtain the geometric shape of the weld pool and weld bead with good results. Sensor fusion integrates several sensing technologies in the same monitoring system. **Figure 14** shows the literature review statistics, obtained in [7], about the use of indirect monitoring technologies to estimate the weld bead geometry.

2.5.1 Modeling and estimating

Some of these measuring methods need a model to obtain the desired information from the process. To obtain a representative model, the estimators have been used successfully under specific conditions. But it is imperative to create a model that can be easily programmed and fed into the control system. The model must have satisfactory precision in the prediction of the depth of the weld bead and cover all of the positions used in the welding work. It is very useful if it also represents a wide range of thicknesses of the material, but this is not always possible.

The research about modeling the weld bead depth tries to relate this variable with the welding electric current intensity, welding voltage, wire feed speed, and welding speed. Documents analyzed in [7], show that the research is making mainly in horizontal or flat welding to obtain static models and the researchers are using artificial intelligence algorithms. The most used methods to estimate the weld bead geometry

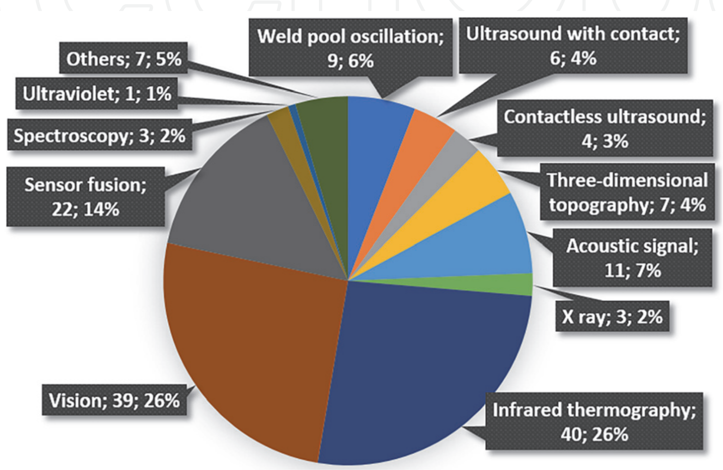

Figure 14.
Literature review statistics about indirect monitoring technologies used to obtain measurements of the weld bead geometry [7].

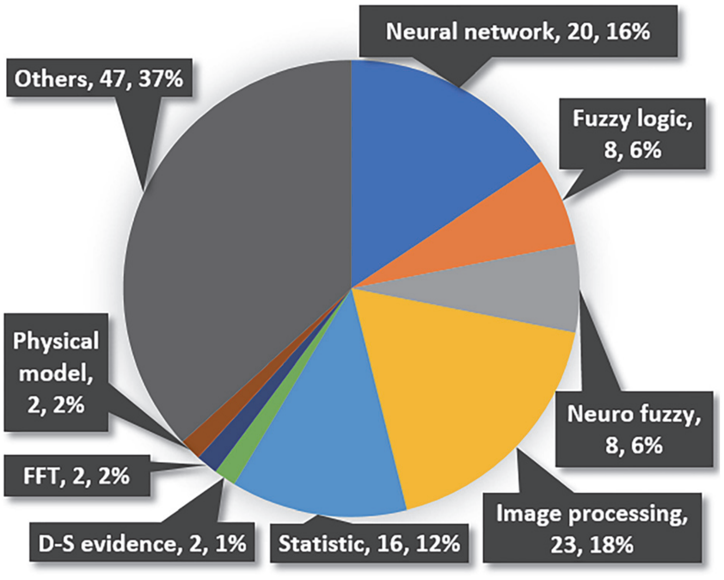

Figure 15.
Literature review statistics about analysis method used to estimate the weld bead geometry [7].

are artificial neural networks, fuzzy logic, and their combinations. This group represents 28% of the works, as shown in **Figure 15**. Image processing and statistical techniques such as multiple regression analysis, least squares, or factorial design are also frequently used. All these make up 58% of the total of the publications found.

In the welding process, the thermal energy is supplied through an electric current and stored in the material. Due to thermal inertia, dynamic models can be a better representation of the process. In these models, the historical values of the welding parameters are also selected as inputs. Dynamic behavior is essential to estimate the current and future state form to the past state. Despite this, [7] shows dynamic models in a minority. The main cause of the selection of the static model is the difficulty in obtaining a continuous data set of the weld bead depth. One way to obtain it is to perform a longitudinal cut and a macrographic analysis on the weld bead with an image processing algorithm as made in [22]. In the traditional cross-section cut, it is not possible to obtain enough information to make a dynamic model.

2.5.2 Sensor fusion

Measurements obtained by several sensors or measuring systems can be used to estimate the values of other or the same magnitudes. These techniques that combined different sensing technologies or information sources to obtain better sensing results are named sensor fusion or fusion sensory data. The sensor fusion is a multilevel process that needs a model to combine the information and describe the static or dynamic behavior of processes.

There are applications in different spheres such as aerial and ground navigation of mobile robots, systems for environmental monitoring, visual sensor networks, medicine, security, fault detection, and quality control, among others, as shown in [23]. This is a relatively young research area, but it is the third method used for the indirect monitoring of the welding process, as shown in **Figure 14**. In recent years, these methods have been studied to achieve effective welding and sense of the weld bead.

The sensor fusion can be classified in different ways as discussed in [24]. One of the most representative classifications for welding processes is *according to the relationships of the input data*, which defines how the information relates between the sensors. It can be complementary, competitive or redundant, and cooperative,

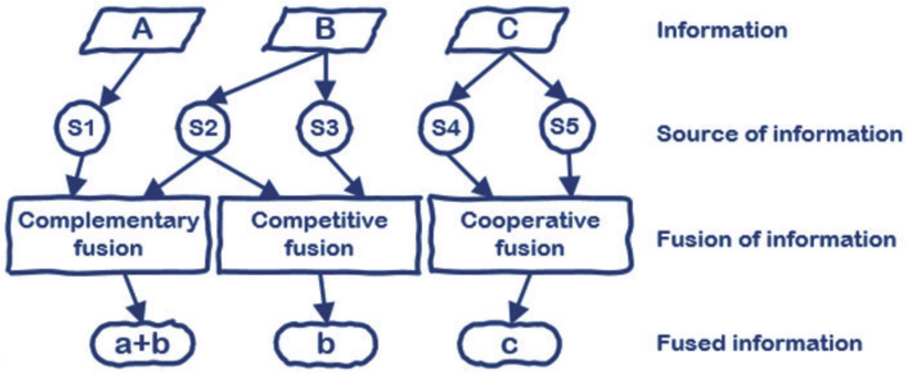

Figure 16.
Classification according to the relationships of the input data (adapted from [24]).

as shown in **Figure 16**, but it is very common to find more than one way of working on the same group of sensors.

Figure 16 shows four levels of the fusion process. The following list exemplifies welding process parameters:

- Information level represents the input magnitudes and zones that are measured by sensors, for example, the weld bead and weld pool dimensions.
- Source of information is the sensors installed on the process, for example, the video and thermographic cameras.
- The fusion of information is the algorithms used to obtain the fused information, for example, an image processing and neural network algorithms.
- Fused information is the final result, for example, the weld bead depth.

The *complementary fusion* is about fusing incomplete information that is obtained starting from different sources. This is the case in that several sensors are measuring different parts of an atmosphere or phenomenon, covering a bigger area, and allowing a more complete and more global vision of the process. For example, you can combine the weld pool thermographic information (A) obtained from an infrared camera ($S1$) and weld bead dimensions (B) obtained from a video camera ($S2$) to calculate the weld pool dimensions ($a + b$).

In *competitive or redundant fusion*, all the sensors are monitoring the same area, working redundantly and competitively. These sensors can have similar or different measurement principles. An example is the dimensional information (B) about the weld bead obtained from two video cameras ($S2$ and $S3$) used to calculate the weld bead dimensions (b).

Cooperative or coordinated fusion uses the information from independent several sensors to obtain new information, for example, the combination of the information of the weld bead (C) obtained from a vision system ($S4$) and pyrometer ($S5$) to estimate the weld bead penetration value (c).

A cooperative sensor fusion algorithm is used in [22] to obtain an estimator of the weld bead depth $\hat{D}$ for GMAW process. The developed algorithm tries to obtain information about the amount and spatial distribution of the energy supplied to the workpiece to estimate the depth of the weld bead using a thermographic camera and welding electric current measurements. The fusion algorithm is based on a perceptron neural network that combines the infrared features T of the weld molten pool, the welding current in the actual $i(nT)$ and previous sample $i(nT - T)$, and previous depth estimation $\hat{D}(nT - T)$. The symbol T is the sample time and n is the sample number. These previous values allow capturing the dynamic behavior of the process.

The artificial neural network has 8 neurons in the input layer, 12 neurons in the hidden layer, and 1 in the output layer. The activate function is the hyperbolic tangent sigmoid transfer function. The network training should be done with experimental measurements of the parameters of input and output and by using the backpropagation algorithm. A block diagram is shown in **Figure 17**.

The thermographic matrix, supplied by the thermographic camera, is processed with a moving average filter to obtain the thermographic peak T_p, base plane T_b, thermographic curve width T_w, thermographic area T_a, and thermographic volume T_v. The thermographic image is taken on the weld pool area as a physical reference, but the welding arc and the electrode are included. These features from a sample are shown in **Figure 18**.

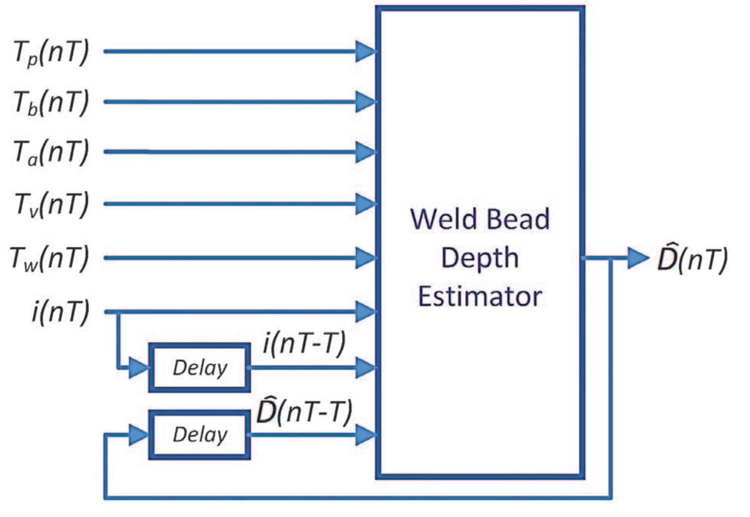

Figure 17.
Weld bead depth estimator block diagram, based on artificial neural network, developed in [22].

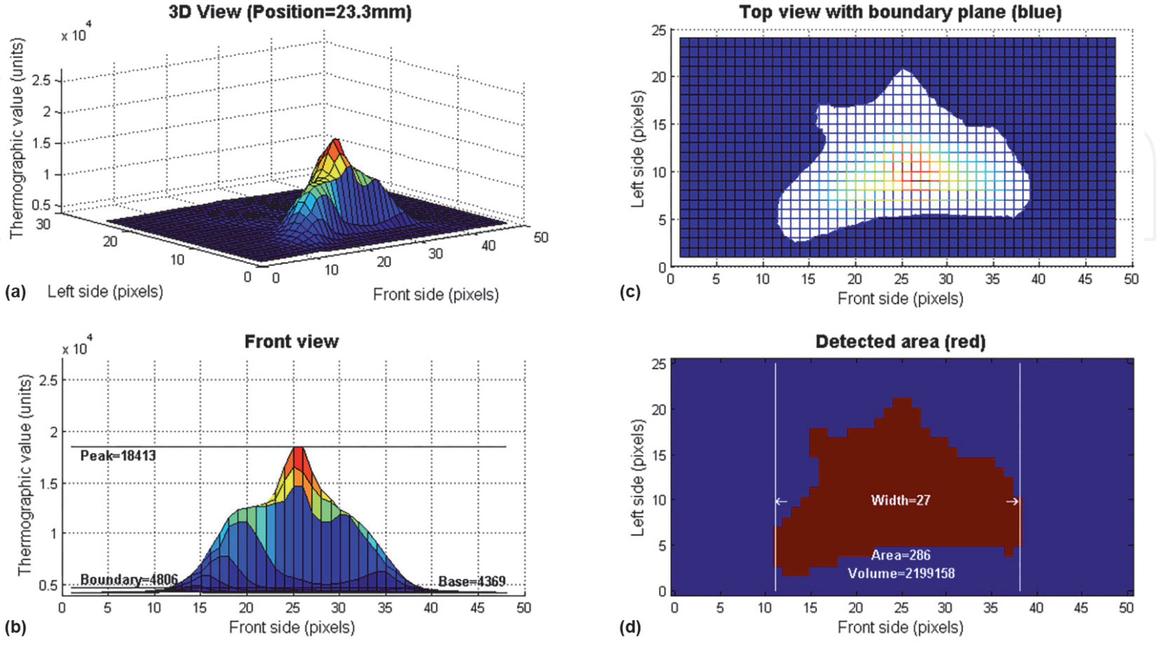

Figure 18.
Features extracted from an infrared image: (a) three-dimensional curve, (b) front view of the curve, (c) intersection between the boundary plane and three-dimensional curve, (d) and the calculation of the width, area and thermographic volume.

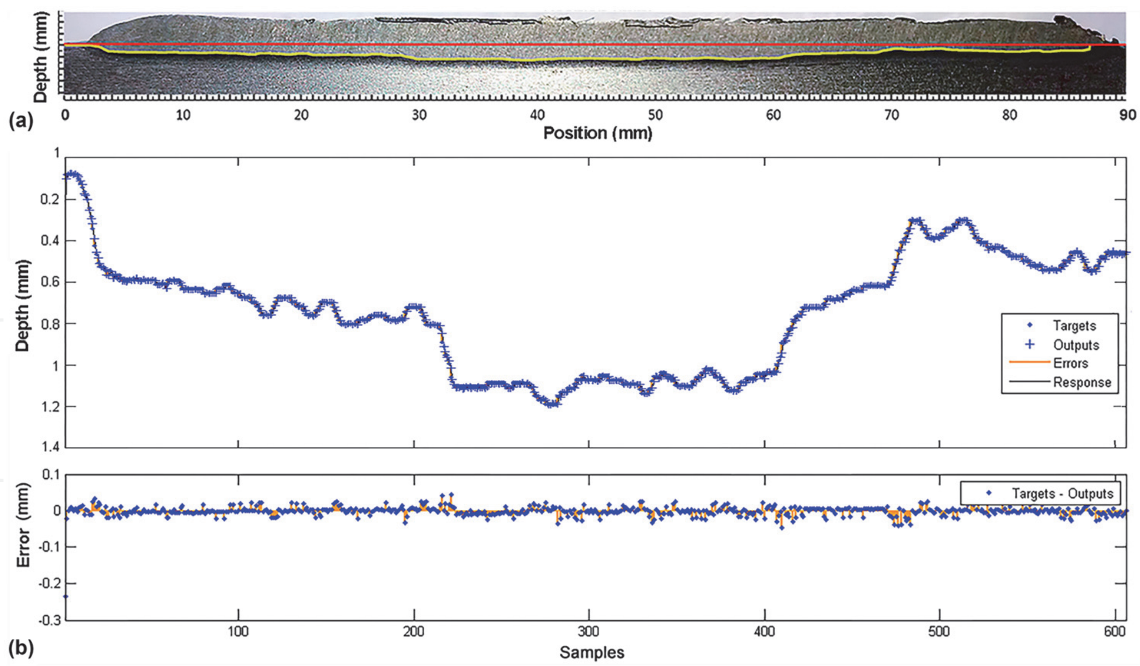

Figure 19.
Results obtained in the estimation of the weld bead depth in [22]: (a) weld bead depth longitudinal profile and (b) model response and experimental measurements. In the sample axis, each value corresponds to a position in the piece.

The base plane is calculated as the average of 10% of the values on the left and right sides, as shown in **Figure 18b**. The boundary plane is 10% above the base plane. The sum of active pixels in the intersection plane between the thermographic surface and the boundary plane is the area. The sum of the thermographic values within the intersection plane is the thermographic volume, shown in **Figure 18d**. This algorithm was optimized for implementation in embedded devices.

A contribution of the method is the minimization of errors when multiple inflection points are found because it does not use the second derivative for the calculation of thermographic width. Also, volume calculations are performed using the actual thermographic curve instead of the ideal Gaussian curve used in most research as an approximation value and using more complex equations. This approach uses only addition operations, simplifies calculations, and improves model accuracy.

The weld bead depth profile to network training was obtained using an image processing algorithm on the macrographic picture of the longitudinal cut of the piece. **Figure 19a** shows 610 measurements of weld bead depth in a yellow line and the base metal surface in a red line. The model has a fit of 0.99844, a performance or median square error (MSE) of 7.61×10^{-4}, and an estimation error less than 0.05 mm (less than 5% of full range). The error curves in **Figure 19b** show a model response that represents the behavior of the process with great accuracy.

It can be noticed that accurate sensing results were obtained based on multi-sensor information fusion technology, due to more weld pool information and effective information fusion techniques.

3. Evolution and comparison of the techniques and methods used for measurement and estimation of the geometry of weld bead

An analysis made in [7] about techniques and methods used for measurement and estimation of the geometry of the weld bead found publications and patents since 1971, but it is not until the 1980s that a greater interest in this subject was observed. Recently, in the last decade, the number of publications is increased. **Figure 20** shows this growing interest.

The technological development and cost reduction of sensors and the need for welding process control in an industrial environment (robotic welding) stimulated the number of scientific works about these topics.

An example is the development of infrared sensors that since the 1970s were available but in the 1980s were given classified contracts by the US Department of Defense to Honeywell and Texas Instruments to develop uncooled infrared sensor technology. In 1992, the US Government de-classified this technology for commercial products, allowing the sale of their devices to foreign countries, but kept close the manufacturing technologies. In the next decade, several countries developed uncooled imaging systems [25] with a drastic reduction of uncooled array cost.

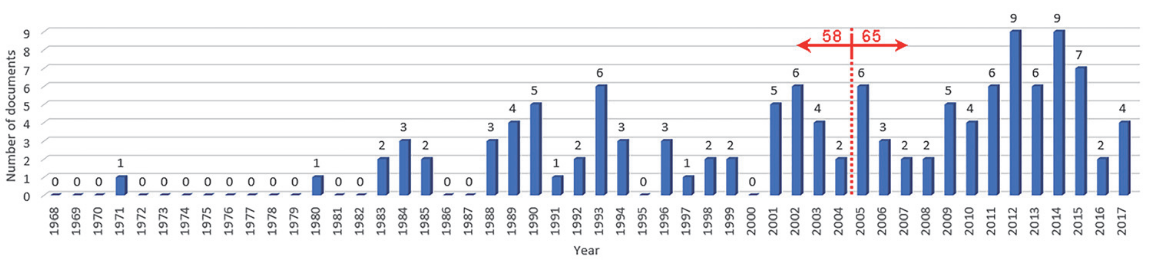

Figure 20.
Evolution of the number of publications about measurement and estimation of the weld bead geometry (adapted from [7]).

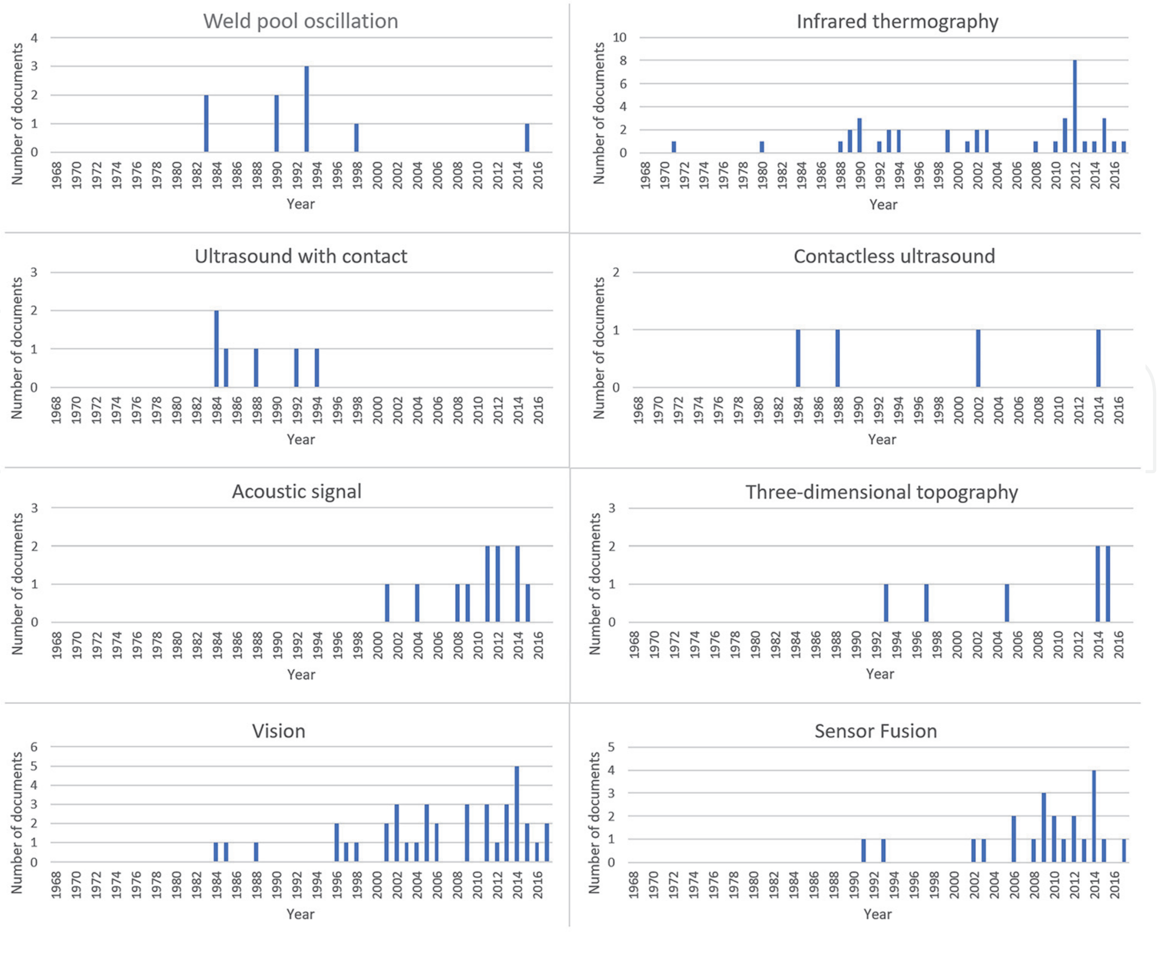

Figure 21.
Evolution of techniques used to measure the weld bead geometry [7].

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Variable	Cost[a]/accuracy[b] of measuring method								
	From welding power source	From robotic system	Laser distance sensor	Laser scanner	Structural light[c]	Pyrometer[d]	Thermographic camera[d]	Acoustic signal[d]	Weld pool oscillation[c]
Welding voltage	L/H								
Welding current	L/H								
Wire feed speed	L/M								
Welding speed		L/H							
Welding angle		L/H							
Orbital angle		L/H							
Contact tip-to-work distance		L/M	M/H	H/H					
Welding joint dimensions				H/H	M/H				
Weld bead width			M/M	H/H	M/H				
Weld bead reinforcement			M/M	H/H	M/H				
Weld bead penetration						M/M	H/M	L/L	M/L

[a]*L—Low cost; M—medium cost; and H—high cost.*
[b]*L—Low accuracy; M—medium accuracy; H—high accuracy.*
[c]*This method is used together with one or several video cameras.*
[d]*This method is used alone or together with welding power source measurements (e.g., arc variables).*

Table 1.
Comparison between the most used methods to measure the variables of welding processes, considering the cost and accuracy of the method.

This evolution can be observed in **Figure 21** with a significant increase in scientific publications in this decade.

The estimation of geometry weld bead using acoustic signal and vision techniques shows more activity in the last 20 years because of the great development of cameras, audio systems, and digital signal processor devices with high speed and quality, little size, and low cost.

In **Table 1**, some commonly used methods to obtain measurements of welding processes online are compared. The comparison criteria are the cost of implementation and the accuracy of the method. Both criteria are evaluated as low, medium, or high. In the table, a blank cell indicates a method that is not used to measure a specific variable. Some methods are used in conjunction with other measurement methods to obtain or estimate the value of the variable. Various measurement methods can be combined using a sensor fusion technique.

The analysis techniques most used in the last century were regression models, least mean square algorithms, Kalman filter, and other statistical methods. In the last few years, the principal techniques used are the artificial neural network, fuzzy logic, and neuro-fuzzy. The intense development of image processing algorithms was observed in the last 20 years.

4. Conclusions

The correct selection of measuring techniques and the use of sensor fusion algorithms, combined with indirect measurement techniques, can help to reduce the cost of welding production and increase productivity by the detection or prediction of many welding defects or set point deviations. These measurements allow online adjusting of the welding power source and robot parameters in a closed control loop. Online estimation of variables that cannot be measured improves control systems and reduces the number of parts rejected in the final quality inspection.

To take advantage of a modern welding power source, it is important to equip the monitoring and control system with serial communication capabilities. The modeling of estimators is a critical step to obtain an accurate measuring system, and dynamic models have a better representation of the welding process than static models due to thermal inertia of the process. Vision and thermographic measuring techniques, image processing, and neural network algorithms, despite consuming more computing resources, are the most used to estimate the weld bead geometry, and excellent results have been observed.

The research on sensor fusion algorithms is grown. Following this trend, in this work a novel modeling method that uses arc welding measurements and thermographic information to create a dynamic model to estimate the weld bead penetration is presented. This new approach obtains information about the amount and spatial distribution of the energy in the workpiece and uses only addition operations, simplifies calculations, and improves model accuracy. A satisfactory solution was shown to be applied in welding automatic control using computers or embedded devices.

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