

METHOD AND SYSTEM FOR ROBOTIC MULTI-PASS WELDING FOR FILLING COMPLEX GEOMETRY USING WELD PROFILE CONTROL WITH DATA- DRIVEN FAST INPUT ALLOCATION

BACKGROUND

5 Technical Field

Embodiments of the invention relate to multi-pass welding for complex weld geometry and particularly to using weld profile control with data-driven fast input allocation for robotic welding which is capable of compensating for environmental disturbances or system uncertainties and achieving filling profile with increased accuracy and improved
10 aesthetics.

Description of Related Art

Multi-pass welding is a time-consuming manufacturing procedure in the marine and offshore industry for joining thick materials. In addition, it requires very skilled welders to produce acceptable welding profile on the weld geometry. As such, robotic multi-pass
15 welding is advantageous and essential for increasing productivity. Besides, the robotic welding system has to be sufficiently robust in view of uncertainties such as variation in weld geometry due to assembling process.

Numerous research in multi-pass welding has been carried out on modeling the weld bead distribution [1] and [2]. Recently, robotic path planning utilizing advanced algorithms [3]
20 for multi-pass welding involving regular weld geometries have been proposed. An on-line adaptive fill algorithm is proposed in [4] using a laser vision sensor and multiple torches to achieve proportional feedback control in multi-pass welding. However, the aforementioned solutions are still difficult and impractical to achieve complex geometry welding.

A typical complex weld geometry is shown as in Fig. 1. It is commonly known as
25 thick wall pipe-to-pipe joint. In order to fill the gap for the pipe-to-pipe joint, multi-pass welding is necessary. As discussed in [5] [8], during the multi-pass welding, the torch tracks the previous pass in order to weld the subsequent pass, but the error of each pass will propagate to the subsequent passes. In [8], the error propagation can be suppressed on a flat plate welding using the torch traveling speed as the control parameter for compensating the
30 error of previous pass with experimental verification. For complex weld geometries on the

contrary, not only the error propagation needs to be compensated by adjusting torch traveling speed, but other welding inputs particularly torch weaving parameters need to be changed correspondingly in order to maintain good weld quality during the compensation. In [17], an online path planning algorithm is proposed for the welding of pipe-to-pipe joint, and the welding parameters are calculated based on a simple proportional model. The proposed method in [17] is not verified by experiments and weld quality for the weld parameters is not considered. In [18] and [19], weld quality regarding appropriate combination between torch traveling speed and weaving parameters are studied using analytical model and FEM simulations. However, building these kind of analytical models is complicated especially for welding on complex geometries.

Table 1 below shows a comparison between the capabilities of offline planning-based filling and online tracking-based filling.

Table 1

Capability		Offline Planning-Based Filling	Online Tracking-Based Filling
1	Half-Overlapping	NO	YES
2	Weld Seam Tracking	NO	YES
3	Weld Pool Monitoring	NO	NO
4	Desired Filling Profile	YES	NO
5	Adjustable Torch Traveling Speed	NO	NO
6	Compensating both Repetitive and Non-Repetitive Disturbances	NO	NO
7	Related prior patents / patent application publications	CN 105171289 A US 5841104 A	CN 104002021 A CN 1600488 A

In view of the above and other issues, it would be highly desirable to provide improved multi-pass welding methods which would achieve the capabilities listed in rows 1 to 7 of Table 1.

5 SUMMARY

This disclosure relates to robotic welding for thick and complex weld geometry. To achieve good weld quality, desired welding profile and appropriate welding inputs are both required. In this disclosure, a welding profile control with data driven fast input allocation (PC-FIA) algorithm is proposed for robotic multi-pass welding on a complex weld geometry, namely, pipe-to-pipe joint. The H-infinity (H_∞) feedforward control algorithm is used for the welding profile control. In addition, the allocation of welding inputs including torch traveling speed and weaving parameters are formulated as a max – min problem based on the identified weld input constraint using a data-driven approach. Experimental results show that the filling profile using the proposed method achieves 60% decrease of RMSE with respect to the planned reference, as compared to the case of without using the proposed PC-FIA method. In addition, the allocated weaving parameters ensure that the welding inputs are always maintained within the polyhedral constraint and the whole welding quality is acceptable by industry standard.

In certain experimental results, the final filling profile using the proposed method achieves 60% decrease of RMSE with respect to the planned reference, as compared to without using proposed PCFIA method. In addition, the allocated weaving parameters ensure that the weld inputs are always maintained within the polyhedral constraint.

According to a first aspect of the invention, a method of robotic multi-pass welding on a complex weld geometry by a welding torch is provided, the method comprising:

- (a) ascertaining a feedforward controller function;
- (b) using machine learning training of a plurality of welding input vectors, ascertaining a plurality of desirable welding input vectors therefrom, each of the plurality of welding input vectors having parameters which include inverse travelling speed of the welding torch, weaving width of the welding torch, and weaving length of the welding torch;

(c) ascertaining a current inverse travelling speed of welding torch for a current pass based on at least a position error and the feedforward controller function;

(d) ascertaining an optimized welding input vector from the plurality of desirable welding input vectors wherein the optimized welding input vector includes the current inverse travelling speed; and

(e) performing robotic welding based on parameters of the optimized welding input vector,

wherein step (a) includes ascertaining the feedforward controller function F based on a H-infinity (H_∞) controller which satisfies a minimisation problem as follows

$$\begin{aligned} \min_F \quad & \left\| \frac{1}{FP} \right\|_\infty \\ \text{s.t.} \quad & \|1 - FP\|_\infty < 1 \end{aligned}$$

wherein P is a low order and linear time invariant (LTI) model.

With reference to the first aspect, in a first possible implementation manner of the first aspect, the position error is ascertained based on a difference between a reference welding profile of a previous layer and the actual welding profile of the previous layer.

With reference to the first aspect, in a second possible implementation manner of the first aspect, the reference welding profile is ascertained based on the weld geometry and a count of planned layers of weld.

With reference to the first aspect, in a third possible implementation manner of the first aspect, the method, wherein after performing robotic welding, further comprises:

upon ascertaining a current layer is complete, detecting an actual welding profile of the current layer for ascertaining a next position error for a next layer subsequent to the current layer; and

repeating steps (c), (d) and (e) for the next layer.

With reference to the first aspect, in a fourth possible implementation manner of the first aspect, the method, wherein after performing robotic welding, further comprises:

upon ascertaining a current layer is incomplete, repeating steps (c), (d) and (e).

With reference to any of the first aspect, the first to the fourth possible implementation manner of the first aspect, in a fifth implementation manner of the first aspect, step (b) includes using a polyhedral machine learning algorithm for machine learning training of the plurality of welding input vectors.

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With reference to any of the first aspect, the first to the fifth possible implementation manner of the first aspect, in a sixth implementation manner of the first aspect, step (c) includes ascertaining the current inverse travelling speed of welding torch for a current pass based on

$$v^{-1}(k) = e^{l-1}(k)F + v_c^{-1}(0)$$

10 wherein $v^{-1}(k)$ is the current inverse travelling speed at time sample k, $e^{l-1}(k)$ is the position error, F is the feedforward controller function, and $v_c^{-1}(0)$ is a constant.

According to a second aspect of the invention, a robotic welding system for performing multi-pass welding on a complex welding geometry is provided, the system comprising:

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a welding torch and a robot manipulator supporting the welding torch;
at least one sensor;

a computing unit communicably coupled to the robot manipulator and the sensor;

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a memory storage communicably coupled to the computing unit and includes computer-executable instructions to:

(a) ascertain a feedforward controller function;

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(b) using machine learning training of a plurality of welding input vectors, ascertain a plurality of desirable welding input vectors therefrom, each of the plurality of welding input vectors having parameters which include inverse travelling speed of the welding torch, weaving width of the welding torch, and weaving length of the welding torch;

(c) ascertain a current inverse travelling speed of welding torch for a current pass based on at least a position error and the feedforward controller function; and

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(d) ascertain an optimized welding input vector from the plurality of desirable welding input vectors wherein the optimized welding input vector includes the current inverse travelling speed;

(e) control the welding torch and robotic manipulator to perform robotic welding based on parameters of the optimized welding input vector,

wherein the memory storage further includes computer-executable instructions to, in step (a), to ascertain the feedforward controller function F based on a H-infinity (H^∞) controller

5 which satisfies a minimisation problem as follows

$$\begin{aligned} \min_F \quad & \left\| \frac{1}{FP} \right\|_\infty \\ \text{s.t.} \quad & \|1 - FP\|_\infty < 1 \end{aligned}$$

wherein P is a low order and linear time invariant (LTI) model.

10 With reference to the second aspect, in a first possible implementation manner of the second aspect, the memory storage further includes computer-executable instructions to ascertain position error based on a difference between a reference welding profile of a previous layer and the actual welding profile of the previous layer.

15 With reference to the second aspect, in a second possible implementation manner of the second aspect, the reference welding profile is ascertained based on the weld geometry and a count of planned layers of weld.

20 With reference to the second aspect, in a third possible implementation manner of the second aspect, the memory storage further includes computer-executable instructions to after performing robotic welding and upon ascertaining a current layer is complete, detect an actual welding profile of the current layer for ascertaining a next position error for a next layer subsequent to the current layer; and repeat steps (c), (d) and (e) for the next layer.

25 With reference to the second aspect, in a fourth possible implementation manner of the second aspect, the memory storage further includes computer-executable instructions to after performing robotic welding and upon ascertaining a current layer is incomplete, repeating steps (c), (d) and (e).

30 With reference to any of the second aspect, the first to the fourth possible implementation manner of the second aspect, in a fifth implementation manner of the second

aspect, the memory storage further includes computer-executable instructions to, in step (b), use a polyhedral machine learning algorithm for machine learning training of the plurality of welding input vectors.

With reference to any of the second aspect, the first to the fifth possible implementation manner of the second aspect, in a sixth implementation manner of the second aspect, the memory storage further includes computer-executable instructions to, in step (c), ascertain the current inverse travelling speed of welding torch for a current pass based on

$$v^{-1}(k) = e^{l-1}(k)F + v_c^{-1}(0)$$

wherein $v^{-1}(k)$ is the current inverse travelling speed at time sample k, $e^{l-1}(k)$ is the position error, F is the feedforward controller function, and $v_c^{-1}(0)$ is a constant.

BRIEF DESCRIPTION OF THE DRAWINGS

Embodiments of the invention are disclosed hereinafter with reference to the drawings, in which:

Fig. 1 shows a complex weld geometry of a thick wall pipe-to-pipe joint prior to welding;

Fig. 2A shows a physical arrangement of a robotic welding system;

Fig. 2B shows a schematic arrangement of a robotic welding system;

Fig. 3 shows multi-pass planning for a thick wall pipe-to-pipe weld geometry;

Fig. 3 shows a weld geometry of a brace-to-chord joint;

Fig. 4A shows a torch tracking a previous seam boundary for each pass;

Fig. 4B shows a top view from the standing pipe;

Fig. 5 shows multi-pass filling of each layer using a robotic welding system;

Fig. 6 shows Zig-Zag weaving motion for robotic welding at each time sample (cycle);

Fig. 7A shows a block diagram for a welding profile control system according to one embodiment;

Fig. 7B shows a block diagram for a welding profile control system according to another embodiment;

Fig. 8 shows a PC-FIA method according to one embodiment;

Fig. 9 shows an identified polyhedral constraint region;

5 Fig. 10 shows a welding result of the final filling layer without having employed the PC-FIA method;

Fig. 11 shows a welding result of the final filling layer having employed the PC-FIA method;

10 Fig. 12 shows a comparison of welding inputs of the bottom pass of final layer, respectively with PC-FIA and without PC-FIA;

Fig. 13 shows a comparison of the input, namely, with proposed PC-FIA, with PC algorithm only, and without PC-FIA methods;

Fig. 14A, Fig. 14B and Fig. 14C show laser scan samples of the final filling layer profile without PC-FIA method on the angle positions 36°, 56° and 76° respectively; and

15 Fig. 15A, Fig. 15B and Fig. 15C show laser scan samples of the final filling layer profile without PC-FIA method on the angle positions 36°, 56° and 76° respectively.

DETAILED DESCRIPTION

20 In the following description, numerous specific details are set forth in order to provide a thorough understanding of various illustrative embodiments of the invention. It will be understood, however, to one skilled in the art, that embodiments of the invention may be practiced without some or all of these specific details. In other instances, well known process operations have not been described in detail in order not to unnecessarily obscure pertinent
25 aspects of embodiments being described. In the drawings, like reference numerals refer to same or similar functionalities or features throughout the several views.

Embodiments described in the context of one of the methods or devices are analogously valid for the other methods or devices. Similarly, embodiments described in the context of a method are analogously valid for a device, and vice versa.

30 Features that are described in the context of an embodiment may correspondingly be applicable to the same or similar features in the other embodiments. Features that are described in the context of an embodiment may correspondingly be applicable to the other embodiments, even if not explicitly described in these other embodiments. Furthermore, additions and/or combinations and/or alternatives as described for a feature in the context of

an embodiment may correspondingly be applicable to the same or similar feature in the other embodiments.

As used herein, the articles “a”, “an” and “the” as used with regard to a feature or element include a reference to one or more of the features or elements.

5 As used herein, the terms “first”, “second”, and “third,” etc. are used merely as labels, and are not intended to impose numerical requirements on their objects.

As used therein, the term “coupled” and related terms are used in an operational sense and are not necessarily limited to a direct physical connection or coupling. Thus, for example, two devices may be coupled directly, or via one or more intermediary devices. In certain
10 examples, devices may be suitably coupled such that information or signal can be passed therebetween, while not sharing any physical connection with each other. Based on the present disclosure, a person of ordinary skill in the art will appreciate a variety of ways in which coupling exists in accordance with the aforementioned definition.

As used herein, the term “ascertain” may include at least one or more of the following
15 steps: computing / calculating, identifying and selecting.

I. ROBOTIC MULTI-PASS WELDING FOR COMPLEX GEOMETRY

A. Complex Weld Geometry: Thick Wall Pipe-to-Pipe Joint

In order to have a good welding quality for thick materials such as the aforementioned
20 thick wall pipe-to-pipe joint, the weld geometry has to be filled layer by layer until the desired reference filling profile ends at the point P_f as shown in Fig. 3. The standard for the desired filling layer profile is detailed in [20]. With the robotic welding system according to the present disclosure, it is necessary to have a reference filling plan for each layer and each pass of the multi-pass welding.

25 In this disclosure, due to the layout of all layers and passes are considered to be evenly distributed, the reference profile for each layer can be calculated by equally dividing the weld geometry with the number of planned layers L . In addition, considering each subsequent layer has one more pass than the previous layer, the reference welding trajectory (cross section) of each pass can be illustrated as in Fig. 3.

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B. Robotic Multi-Pass Welding

According to one aspect of the invention, a robotic welding system (see Fig. 2B) comprises: a welding torch, at least one sensor, a robot manipulator, a memory storage, a computing or processor unit communicably coupled to the robot manipulator, the memory storage and the sensor(s). The welding torch may be supported by the robotic manipulator. The welding torch may be controlled by the robot manipulator which may be communicably coupled to the torch and the computing unit and configured to control the movements or motion of the torch based on instructions received from the computing unit. The at least one sensor may comprise a detector, e.g. laser scanner, configured to detect the seam boundary of previous pass which is also the toe-line of the welding, and/or a monitoring device, e.g. camera, configured to monitor the welding pool in order to measure the bead width in real-time. The at least one sensor may be communicably coupled to the memory and/or computing unit to transfer data thereto for storage and/or processing respectively. The memory storage may store data, e.g. from the sensor and/or computing unit, and computer-executable instructions for implementing robotic multi-pass welding in accordance with various embodiments of the invention.

Fig. 2A shows a possible physical arrangement of a robotic welding system in practice. The detector, e.g. laser scanner, may be positioned beyond the torch, while the monitoring device, e.g. camera, may be positioned behind the torch.

Using a robotic welding system according to the present disclosure, the detector, e.g. laser sensor scans the weld profile after welding of each layer. Based on the scanned profile, the welding trajectories for the next layer are planned using the offset of the original reference. For each pass of the new layer, the torch tracks the welding trajectory identified on the previous profile to generate a new pass as illustrated in Figs. 4A and 4B. As such, for each layer of welding, as the welding trajectory for each pass are exactly on the previous welding layer profile, the torch is able to track closely with the previous welded profile in order to achieve required overlapping among layers.

Robotic welding according to the present disclosure addresses two challenges: (1) achieving desired welding profile; and (2) maintaining appropriate weaving motion.

(1) Achieving Desired Welding Profile:

As an objective of welding the complex geometry is to fully fill the gap with a desired filling profile, the welding profile of each layer must be appropriately controlled. Considering

the control of welding process is a discrete-time process. For a discrete time sample k , the cross section showing the actual welding profile of a layer and its corresponding reference profile is illustrated in Fig. 5.

In Fig. 5, the welding trajectories of each pass in layer l are actually on the welding profile of layer $l - 1$ as the torch will track the profile of previous layer closely in order to weld the passes in subsequent layer. Noted that all the scalars r_i^j and y_i^j are the positions of the weld trajectories cross-section points in y-axis. As such, the profile of a layer, say layer l , can be expressed by a L-dimensional (L is defined in Fig. 3) vector

$y^l = [y_1^l(k), y_2^l(k), \dots, y_i^l(k), y_{l+1}^l(k), 0, \dots, 0]^T$ Similarly, the L-dimensional vector $y^{l-1}(k)$ can express the profile of layer $l - 1$.

By tracking $y^{l-1}(k)$, passes in layer l are welded and each of the bead leg length $y_{wp}^l(k), p \in \{1, \dots, l\}$ is added on $y^{l-1}(k)$. Noted that one more pass is normally added at the top of a new layer. As such, the difference between $y^{l-1}(k)$ and $y^l(k)$ can be denoted by

$$y_w^l = [y_{w1}^l(k), y_{w2}^l(k), \dots, y_{wl}^l(k), y_{l+1}^l(k), 0, \dots, 0]^T$$

where $y_{l+1}^l(k)$ is considered as the top intersection point of the profile $y^l(k)$ and the gap as shown in Fig. 5. Noted that in practice a new layer may have the same number of passes as the previous layer and $y_{l+1}^l(k) = 0$ in that case. As such, the welding from $y^{l-1}(k)$ to $y^l(k)$ can be expressed as $y^l(k) = y^{l-1}(k) + y_w^l(k)$ – equation (1)

For the whole cross section at time sample k , the welding profiles of all the L layers can be expressed as

$$\mathbf{Y}(k) = \begin{bmatrix} y_1^1(k) & \dots & y_1^{l-1}(k) & y_1^l(k) & \dots & y_1^L(k) \\ y_2^1(k) & \dots & y_2^{l-1}(k) & y_2^l(k) & \dots & y_2^L(k) \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & y_l^{l-1}(k) & y_l^l(k) & \dots & y_l^L(k) \\ 0 & \dots & 0 & y_{l+1}^l(k) & \dots & y_{l+1}^L(k) \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & 0 & 0 & \dots & y_{L+1}^L(k) \end{bmatrix}$$

– equation (2)

where the row of $\mathbf{Y}(k)$ denotes the layer space and the column of $\mathbf{Y}(k)$ represents the pass space of a layer. In particular, each layer profile $y^l(k)$ is represented by the l th column of $\mathbf{Y}(k)$. As the welding of passes within a layer is started from the bottom and the molten metal

during welding will overlap its bottom pass by gravity itself, the welding trajectories' position of each pass on z-axis within a layer are only need to be planned with fixed offset as shown in Fig. 5. As such, we only consider the position error of each weld profile on y-axis in this application.

As our robotic welding system will track the previous layer profile when welding the next layer, the error of layer $l - 1$'s welding profile $e^{l-1}(k) = r^{l-1}(k) - y^{l-1}(k)$ will propagate to layer l and all the subsequent layers, which is known as error propagation as shown in Fig. 5. In order to achieve an appropriate filling layer profile and suppress the profile error propagation, the size of each pass must be well controlled by adjusting the welding input parameters such as torch traveling speed. However, other input parameters such as weaving parameters must be changed accordingly in order to maintain good weld quality for each of the pass.

2) Maintaining Appropriate Weaving Motion:

When the torch traveling speed is changed, the torch weaving motion during welding has to be adjusted appropriately in particular for complex weld geometry [18] [19]. With appropriate weaving, the molten metal in the weld pool will be evenly pushed to both sides of the workpiece and the appearance of the weld bead will be rather uniform during the changing of torch speed. Without good weaving, the joining of workpiece after welding will be weak and prone to the occurrence of crack. In this disclosure, Zig-Zag weaving is used as illustrated in Fig. 6. It is well known that the torch weaving motion can be seen as a sinusoid or triangle wave determined by two parameters: amplitude α (mm) and frequency ω (Hz).

In examples of existing industrial robotic welding systems, weaving width and length, i.e., 2α and $\frac{v}{\omega}$, are commonly used as the inputs for weaving parameters as illustrated in Fig. 6.

As such, we define the welding input vector $u(k)$ at time sample k as below

$$u(k) = \left[v^{-1}(k), \quad 2\alpha(k), \quad \frac{v(k)}{\omega(k)} \right]^T \quad \text{--equation (3)}$$

It is to be noted that $v^{-1}(k)$ is used as it is the control input parameter in Section II relating to profile control with fast input allocation (PC-FIA) methodology. In practice, the weaving parameters will be updated after each weaving cycle of about one second. In order to have an appropriate assignment of $u(k)$ such that good welding quality is maintained, it is naturally to consider there is a constraint region U for the input vector $u(k)$. As all the input parameters are bounded, U is a convex and enclosed region such that $u(k)$ is a good or

desirable combination if and only if $u(k) \in U$. As such, an objective of this disclosure is to identify the constraint region U and assign the input parameters $u(k)$ within U .

II. PROPOSED PROFILE CONTROL WITH FAST INPUT ALLOCATION (PC-FIA)

5 METHODOLOGY

In this section, a welding profile control algorithm is carried out for the robotic multi-pass welding formulated in Section I. In addition, a fast data-driven input parameters allocation algorithm is proposed based on the identified weld input constraint.

10 A. Weld Profile Control (PC) Algorithm

Assume that all the welding inputs except the torch traveling speed are maintained as constant and there is no constraint for these inputs. In this case, the compensation and suppression of error propagation in multi-pass welding can be formulated as a linear control problem. In this paper, as the whole welding profile of each layer is controlled, the control system becomes multi-input multi-output (MIMO). However, due to the welding of each pass within a layer is independent, i.e., the input-output pairs in this application are all decoupled. Fig. 7A shows a proposed control block diagram according to one embodiment. In Fig. 7A, the control of each pass is using both the real-time feedback error $e(k)$ and error from previous pass $e(k - N_k)$ with N_k being assumed as a time delay between two passes. As the welding is on flat plates, $e(k)$ is measurable in real-time in this case and the details are referred in Section IV.

In this embodiment of Fig.7B, however, as $y_w(k)$ denotes the leg length of the beads as defined in Fig. 5 and cannot be measured directly, the welding profile of each layer can only be measured by the laser scanner after the welding is finished. In this embodiment of Fig. 7B, the block diagram of Fig. 7A is modified by removing the feedback controller $C(z)$ therefrom and maintaining the baseline control input v_c^{-1} as constant. The modified block diagram for welding layer l can be illustrated as in Fig. 7B.

From Fig. 7B, the signal transfer within the block diagram can be written as

$$e^{l-1}(k)FP + v_c^{l-1}(0)P + y^{l-1}(k) + w_n^l(k) = y_n^l(k) \quad \text{--equation (4)}$$

Substituting $y^l(k) = r^l(k) - e^l(k)$ and $y^{l-1}(k) = r^{l-1}(k) - e^{l-1}(k)$ into equation (4), the following equation can be obtained,

$$e^l(k) = e^{l-1}(1 - FP) - v_c^{-1}(0)P + (r^l(k) - r^{l-1}(k)) - w_n^l(k) \quad \text{--equation (5)}$$

By choosing $v_c^{-1}(0) = (r^l(0) - r^{l-1}(0))/P(0)$ where $r^l(0)$ is the initial position of reference weld profile of layer l and $P(0)$ is the static gain of $P(z)$, $v_c^{-1}(0)P$ can be written as

$$v_c^{-1}(0)P = (r^l(k) - r^{l-1}(k) + w_r(k)) \quad \text{--equation (6)}$$

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with $w_r(k)$ denoting the difference between the resulted bead leg length using constant input v_c^{-1} and the reference bead leg length at time sample k .

It is to be noted that w_n^i is the environmental disturbance and is normally non-repetitive, while w_r in (6) can be seen as repetitive disturbance to the welding process. As such, by defining $w^l(k) = w_r(k) + w_n^l(k)$ and ignoring the sign of $w^l(k)$, equation (5) can be expressed as

$$e^l(k) = e^{l-1}(k)(1 - FP) + w^l(k) \quad \text{--equation (7)}$$

Considering the weld profile error of the first layer is zero, the following equation can be obtained from equation (7),

$$\begin{aligned} e^l(k) &= \sum_{i=0}^l (1 - FP)^{l-i} w^i(k) \\ &= \sum_{i=0}^l (1 - FP)^{l-i} w_n^i(k) + \sum_{i=0}^l (1 - FP)^{l-i} w_r(k) \\ &= \sum_{i=0}^l (1 - FP)^{l-i} w_n^i(k) + \frac{1 - (1 - FP)^l}{FP} w_r(k). \end{aligned} \quad \text{--equation (8)}$$

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Noted that if $\|1 - FP\|_\infty < 1$, we have

$$\begin{aligned} \lim_{l \rightarrow \infty} (1 - FP)^l &= 0 \\ \lim_{l \rightarrow \infty} \frac{1 - (1 - FP)^l}{FP} &= \frac{1}{FP} \end{aligned} \quad \text{--equation (9)}$$

As such, in order to achieve the desired filling profile and suppress the profile error propagation during the multi-pass welding, $F(z)$ can be designed such that the following H_∞ minimization problem is satisfied,

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$$\begin{aligned} \min_F \quad & \left\| \frac{1}{FP} \right\|_\infty \\ \text{s.t.} \quad & \|1 - FP\|_\infty < 1 \end{aligned} \quad \text{--equation (10)}$$

The solution of $F(z)$ can be referred to [8]. With the H_∞ feedforward control algorithm, the torch traveling speed of each pass in $v^{-1}(k)$ can be obtained by

$$v^{-1}(k) = e^{l-1}(k)F + v_c^{-1}(0) \quad \text{--equation (11)}$$

For complex weld geometry in this work, not only torch traveling speed needs to be calculated, but appropriate combination of torch traveling speed and torch weaving parameters is required for weld quality as discussed in Section I. As such, the following algorithm is necessary for calculating these input parameters after the torch traveling speed is obtained.

B. Data-Driven Fast Input Allocation (FIA) Algorithm

The allocation for the input parameters based on the calculated inverse torch traveling speed is known as a control allocation problem. Generally, control allocation is a technique such that the allocated control input is equivalent to the original control input and also satisfies specific conditions [7]. In the present embodiment, the control allocation for the input parameters of welding process can be expressed as finding a solution for the following optimization problem:

$$\begin{aligned} & \max_{u(k)} J, \\ & s.t. \quad Bu(k) = Bu_0(k) \\ & \quad u(k) \in U \end{aligned} \quad \text{--equation (12)}$$

where $u_0(k) = [v^{-1}(k), c_1, c_2]^T$ is the original input with $v^{-1}(k)$ and initial setting for the weaving parameters. In addition, $u(k)$ denotes the actual control input after allocation and is defined in equation (3). B is commonly represented as the input gain matrix of the state-space representation of $P(z)$.

It is worth noting that equation (12) is a typical nonlinear program and possibly NP-hard if $u(k) \in U$ is a nonconvex function. Numerous research has been carried out on such nonlinear programs [12]–[14]. In this embodiment, as equation (12) is required to be solved online within a time sample of one second, the main concern is to improve the computational efficiency. As such, finding a convex polyhedron $\hat{U}$ to approximate U is a practical solution for improving the computational efficiency of equation (12). A polyhedron $\hat{U}$ with M hyperplanes can be expressed as

$$\begin{aligned}\hat{U} &= \{W_1 u + g_1 > 0\} \cap \dots \cap \{W_M u + g_M > 0\} \\ &= \{W u + g > 0\}\end{aligned}\quad \text{--equation (13)}$$

where W_m is the m th row of W and g_m is the m th element of g . Considering we have a measured (labeled) training dataset in the input parameter space, and the identification of the polyhedral constraint $\hat{U}$ in equation (13) can be seen as a supervised binary-classification machine learning problem [9]–[11]. The details are introduced in Section III-A.

However, by using such data-driven approach to find $\hat{U}$, there will be always a trade-off between the cost of training dataset and the accuracy of $\hat{U}$. As it is not easy to have a rich dataset in practice, improve the robustness of the computation of $u(k)$ is necessary, i.e., $u(k)$ has the minimum risk to be outside the actual constraint U . For this problem, it is commonly to consider the worst case optimization based on $\hat{U}$ as like [15]. Naturally, the minimum risk solution is to allocate the point $u(k)$ within and far away from the boundary of the region $\hat{U}$, as the worst case is that $\hat{U}$ is an envelope approximation of U .

Assuming that $Bu(k) = Bu_0(k)$ cross through U and $\hat{U}$ for all k . As such, for the polyhedral region $\hat{U}$, considering the minimum (normalized) Euclidean distance between the point $u(k)$ and the boundary of $\hat{U} = \{W_u + g > 0\}$ can be represented by $P(u, \hat{U})$ which is written as

$$P(u, \hat{U}) = \min_{m \in \{1, \dots, M\}} |W_m u + g_m| / |W_m| \quad \text{--equation (14)}$$

As such, if it is to be ensure $u(k)$ being allocated far away from the boundary of $\hat{U}$, the cost function in equation (12) is chosen as

$$J = P(u, \hat{U}) \quad \text{--equation (15)}$$

As $Wu + g > 0$ is required to be satisfied, the control allocation problem or equation (12) can be converted to the following max–min problem

$$\begin{aligned}& \max_u \min_m (W u(k) + g) / |W|, \\ & s.t. \quad Bu(k) = Bu_0(k), \\ & \quad Wu(k) + g > 0.\end{aligned}\quad \text{--equation (16)}$$

In most control allocation theories, the constraint $Bu(k) = Bu_0(k)$ ensures $u(k)$ is equivalent to $u_0(k)$ for the control performance. Further details can be found in [6], [7] and the details are omitted for brevity. In this disclosure, as the weaving parameters have insignificant effect on the output of $P(z)$, $B = [1, 0, 0]$ is used in the experiments described in

Section III. As such, equation (16) is a Mixed Integer Linear Programming (MILP) and can be transformed into a standard linear programming.

It is worth noting that the computational complexity of the MILP problem in equation (16) mainly depends on the number of hyperplanes in $\hat{U}$. The polyhedral machine learning method introduced in Section III-A will ensure the least-number hyperplane of $\hat{U}$. In addition, the proposed allocation design or equation (16) provides the largest tolerance for the system to against the inaccurate approximation of $\hat{U}$. The whole proposed PC-FIA algorithm is summarised in Fig. 8.

In block 81 of Fig. 8, a feedforward controller function is ascertained, such as using equation (10).

In block 82, machine learning is performed, such as based on equation (13) and/or using polyhedral machine learning algorithm. For example, using machine learning training of a plurality of welding input vectors, a plurality of desirable welding input vectors (or vectors producing good weld quality) are ascertained therefrom, wherein each of the plurality of welding input vectors having parameters which include inverse travelling speed of the welding torch, weaving width of the welding torch, and weaving length of the welding torch.

In block 83, profile control is performed, e.g. a current inverse travelling speed of welding torch for a current pass is ascertained, such as using at least a position error and the feedforward controller function, and/or equation (11).

In block 84, fast input allocation is performed, such as based on equation (16). For example, an optimized welding input vector is ascertained, e.g. selected, from the set of desirable welding input vectors wherein the optimized welding input vector includes the current inverse travelling speed.

In block 85, robotic welding is performed based on parameters of the optimized welding input vector.

In block 86, it is to be ascertained, e.g. by the computing unit, whether the present layer has been completed. If no, block 86 proceeds to block 87. If yes, block 86 proceeds to block 88.

In block 87, data of previous layer is retrieved or ascertained for performing profile control in block 83 for the next time sample $k+1$ and/or repeating blocks 83 to 85 for the next time sample $k+1$.

In block 88, it is to be ascertained, e.g. by the computing unit, whether all layers L have been completed. If all layers L have been completed, the welding operation ends. If all layers L have yet to be completed, block 87 proceeds to block 89.

In block 89, actual welding profile of the present layer is detected and stored, e.g. in the memory storage, for use in performing profile control in block 83 for the next layer $l+1$ and/or repeating blocks 83 to 85 for the next layer $l+1$.

III. EXPERIMENTAL APPLICATION

In this section, the polyhedron constraint region for the welding parameters is identified based on experiment test data. In addition, the experimental results for multi-pass welding of brace-to-cord joint is also carried out. Comparisons among using with and without the PC-FIA methods are discussed.

A. Identification of Welding Input Constraint

In order to collect data for the polyhedron training, the experiment for testing different input parameter combinations $[v^{-1}, 2\alpha, v/\omega]^T$ is done. As it is assumed the constraint is an enclosed region, the experiment was designed with the following procedures. Firstly, a good data point is identified and set as the center of the data space. Based on this center, 14 data points that are far away from the center on the 14 directions (6 on axis and 8 on diagonals including both positive and negative directions) were found or identified, and these 14 points were tested. For each of the 14 points, if it is good, the procedures continued to go far away to find the next point on this direction, and if it is bad, the middle point between the neighboring good and bad point is found or identified as the next point in each direction. This procedure was repeated until the good and bad point are close enough.

Through this experiment, 53 data points are collected for input parameters. In addition, the collected data points are augmented by using over-sampling techniques in order to have good learning performance using polyhedral machine learning algorithm [16]. In existing literature, stochastic gradient decent (SGD)-based learning method is commonly used for the learning of polyhedral machine, though it takes long training time and might easily approach to a local optimum if the initial value is randomly chosen. This disclosure uses a Kmeans clustering algorithm for the bad data points first and trains linear SVMs for each cluster of the bad data points and good data points. By setting an acceptable tolerance for the loss of trained SVMs, a least-number-hyperplane polyhedral machine can be initialized, and then the SGD-based learning algorithm in [9] is used for fine-tuning of the polyhedral machine.

As such, based on the data points, a 9-hyperplane polyhedron can be identified as shown in Fig. 9. In Fig. 9, positive points denotes the parameter combination that result in good weld quality, and negative data points represent the bad quality parameter combination. It can be seen that all the positive data points (producing desirable weld quality) are enclosed within the polyhedral region while all the negative data points (producing undesirable weld quality) are outside the region. The proposed PCFIA algorithm can be used based on this polyhedral constraint.

B. Thick Wall Pipe-to-Pipe Welding Experiments

The experiment results of the pipe-to-pipe welding using the robotic welding system according to embodiments of the invention are carried out. In the experiments, a quadrant of the joint is welded for each method and eight filling layers are welded. In order to have an unbroken welding for a quadrant of the joint, the input parameters must be maintained within the identified constraint region. As such, the PC-FIA method and a verified constant input combination without PC-FIA are used as the two methods for the experimental comparison. The results after the final filling layer are shown for using both methods.

1) Without PC-FIA Method:

By without using the PC-FIA method, the weld input parameters during the multi-pass welding are always maintained at 0.4 s/mm inverse torch traveling speed, 2 mm weaving width, and 1.6 mm weaving length. The welding result after finishing the filling layer is shown as in Fig. 10. The laser scan sample for 36, 56, 76 degree of the quadrant are shown as in Fig. 14. It can be seen from the Fig. 14 that the weld geometry is not full filled and the whole profile leans with respect to the reference full filled profile.

2) With PC-FIA Method:

The multi-pass welding for the quadrant with the PC-FIA method is carried out by using the parameters 0.4 s/mm inverse torch traveling speed, 2 mm weaving width, and 1.6 mm weaving length as the baseline input. In addition, the actual inverse torch traveling speed $v^{-1}(k)$ is saturated at $0.2 \leq v^{-1}(k) \leq 0.6$ s/mm. The result after the final filling layer using the proposed method is shown in Fig. 11. The corresponding laser scan sample for 36, 56, 76 degree of the quadrant are shown as in Fig. 15. It can be seen from Fig. 15 that the weld geometry is full filled and the final filling layer profile is close to the reference profile.

C. Discussion

The welding input parameters chosen from the bottom pass of final layer by using both with and without the PC-FIA method are shown as in Fig. 12. From Fig. 12, it can be seen that the weaving parameters change correspondingly with the inverse torch traveling speed by using PC-FIA. The weaving amplitude increases when the torch traveling speed slows down, which is necessary for manipulate the weld pool appropriately. On the contrary, when the torch speed is faster, the weaving amplitude must decrease as there is no much mass input. In addition, the frequency of weaving during welding is maintained around 1 Hz and not varied too much.

The input combination of using with and without PC-FIA in Fig. 12 are also plotted with the polyhedral constraint as shown in Fig. 13. For comparison, the input combination using the PC algorithm only (maintaining weaving parameters constant: 2 mm weaving width, and 1.6 mm weaving length) is also shown in Fig. 13. It can be seen from Fig. 13 that the input combination of PC-FIA is always within the polyhedral constraint region, while the input combination of PC algorithm only is easily outside of the polyhedron when the inverse torch speed is above 0.5 s/mm or below 0.33 s/mm. As such, the PC-FIA method is necessary especially when the torch traveling speed is changing.

In order to observe advantages of the PC-FIA method, the difference between the resulted final filling profile and its reference profile in Figs. 10 and 11 is measured. Using the root mean square error (RMSE) of each angle position of the resulted final profile with respect to the reference, the results for both with and without PC-FIA methods are shown as in Table 2. From Table 2, the RMSE of final layer profile using the PC-FIA method is decreased by 60%, as compared to without using PC-FIA.

TABLE 2
RMSE OF DIFFERENT APPROACHES

(mm)	With PC-FIA	Without PC-FIA
Final Filling profile	2.41	6.02

IV. FEEDFORWARD FILLING CONTROL ALGORITHM: FILLING STRATEGY WITH REAL-TIME FEEDBACK

In the embodiment of Fig. 7A, multi-pass welding is formulated as a control problem and the controller design method to reduce error propagation is detailed below.

5 A. Controller Structure

In existing literature [21]–[23], the dynamic relationship between the welding parameters and weld bead parameters is commonly modeled using low order and linear time invariant (LTI) models with experiment verifications. Let $P(z)$ denote a LTI model or plant representing the welding process, e.g. dynamic relationship between the welding parameters and the weld bead parameters.

In this disclosure, in order to simulate manual welding, the inverse torch traveling speed is considered as the adjustable welding parameter. In addition, let bead width be the only weld bead parameter measured in the robotic welding. As such, the plant $P(z)$ can be regarded as a single-input-single-output (SISO) system. Considering a welded root pass, a control block diagram for the subsequent multi-pass welding within each layer, according to one aspect of the invention, is as shown in Fig. 7A.

In Fig. 7A, the plant $P(z)$ considering disturbance $w(k)$ can be represented as a state-space model given by

$$\begin{aligned} x(k+1) &= A_p x(k) + B_p v^{-1}(k) + B_{pu} u(k) \\ y_w(k) &= C_p x(k) + w(k), \end{aligned} \quad \text{--equation (17)}$$

where $v^{-1}(k)$ in equation (17) and Fig. 7A denotes the inverse of the torch traveling speed as defined in Fig. 4B, and $u(k)$ represents the wire feed rate which is maintained to be constant. The inverse torch traveling speed v^{-1} has a linear relationship between the system input and output according to [21] and [22]. $y_w(k)$ in equation (17) and Fig. 7A represents the measured half bead width. In addition, $w(k)$ in equation (17) and Fig. 7A represents the disturbance to the half bead width.

In Fig. 7A, it is worth noting that the feedback controller $C(z)$ is designed to regulate seam boundary error in the current pass, and the feedforward controller $F(z)$ is designed to regulate error from previous passes. The control input variable $v^{-1}(k)$ is the sum of $v_1^{-1}(k)$ and $v_1^{-2}(k)$ which denote the outputs from $C(z)$ and $F(z)$, respectively. Besides, $y(k)$, $r(k)$, $e(k)$, $y(k-N_k)$ and $e(k-N_k)$ are as defined in Fig. 16. As illustrated in Fig. 16, the current seam boundary $y(k)$ is generated by adding the half bead width $y_w(k)$ of current pass onto the

previous seam boundary $y(k-N_k)$. As such, $y(k)$ is available for system feedback as $y(k-N_k)$ and $y_w(k)$ are both available.

B. Analysis of Error Propagation

5 From Fig. 7A, the transfer equation for seam boundary is derived as

$$y(z) = r(z) \frac{C(z)P(z)}{1 + C(z)P(z)} + w(z) \frac{1}{1 + C(z)P(z)} + y(z) \frac{z^{-N_k}}{1 + C(z)P(z)} + e(z) \frac{z^{-N_k} F(z)P(z)}{1 + C(z)P(z)} \quad \text{--equation (18)}$$

Considering $e(z) = r(z) - y(z)$, equation (18) can be written as

$$y(z) = r(z) \frac{C(z)P(z)}{1 + C(z)P(z)} + w(z) \frac{1}{1 + C(z)P(z)} + y(z) \frac{z^{-N_k}(1 - F(z)P(z))}{1 + C(z)P(z)} + r(z) \frac{z^{-N_k} F(z)P(z)}{1 + C(z)P(z)} \quad \text{--equation (19)}$$

From equation (19), the transfer function from $y(k-N_k)$ to i is defined as:

10

$$G(z) \triangleq \frac{1 - F(z)P(z)}{1 + C(z)P(z)}. \quad \text{--equation (20)}$$

As such, equation (19) can be expressed as

$$y(k) = Tr(k) + Sw(k) + FPSr(k - N_k) + Gy(k - N_k) \quad \text{--equation (21)}$$

15 where S and T denote the sensitivity and complementary sensitivity transfer functions of the baseline loop, respectively.

Using a series of recursive equations, the number of time samples between the current position and the same position in the previous i th pass can be defined as

$$\begin{aligned}
N_k^{(0)} &= 0 \\
N_k^{(1)} &= N_k \\
N_k^{(i)} &= N_k^{(i-1)} + N_{k-N_k^{(i-1)}}, \quad i \in \mathbb{Z}^+
\end{aligned}
\tag{22}$$

As such, the seam boundary of previous passes can similarly be obtained using equation (21) and is given by

$$\begin{aligned}
y(k - N_k^{(1)}) &= Tr(k - N_{k1}) + Sw(k - N_k^{(1)}) \\
&\quad + FPSr(k - N_k^{(2)}) + Gy(k - N_k^{(2)})
\end{aligned}
\tag{23}$$

$$\begin{aligned}
y(k - N_k^{(2)}) &= Tr(k - N_k^{(2)}) + Sw(k - N_k^{(2)}) \\
&\quad + FPSr(k - N_k^{(3)}) + Gy(k - N_k^{(3)}), \\
&\quad \vdots
\end{aligned}
\tag{24}$$

As a result,

$$\begin{aligned}
y(k) &= \sum_{i=0}^l TG^i r(k - N_k^{(i)}) + \sum_{i=1}^l FPSG^{i-1} r(k - N_k^{(i)}) \\
&\quad + FPSG^l r_0(k) + G^l y_0(k) + \sum_{i=0}^l SG^i w(k - N_k^{(i)}),
\end{aligned}
\tag{25}$$

where l represents the number of welded passes, and $y_0(k)$ and $r_0(k)$ are the actual and reference seam boundary of the root pass, respectively.

From equation (25), it can be seen that the error propagation is mainly caused by disturbances in previous passes $w(k - N_k(i))$, $i = 1, 2, \dots, l$. In order to ensure that error propagation can be reduced over all frequencies, the following condition must be satisfied according to [24]:

$$\|SG^i\|_{\infty} < 1, \quad i = 1, 2, \dots, l.
\tag{26}$$

Due to $\|S\|_{\infty} \geq 1$, (12) will be satisfied if

$$\|SG\|_{\infty} < 1.
\tag{27}$$

It is worth noting that the error propagation is contained (e.g. suppress error propagation caused by both repetitive and non-repetitive disturbances) if $|S(z)G(z)| < 1$. As

such, $\|SG\|_\infty$ is used instead of $\|SG\|_2$ in this application. As such, the control objectives are summarized as:

- i) design a feedback controller $C(z)$ such that $y(k) \rightarrow r(k)$ as $k \rightarrow \infty$;
- ii) design a feedforward controller $F(z)$ such that $\|S(z)G(z)\|_\infty < 1$.

5

C. Design of Controller $F(z)$

For the first objective, a PI (proportional-integral) controller $C(z)$ is designed to ensure that the baseline loop is stable and its steady-state error is zero. For the second objective, a causal controller $F(z)$ will be obtained using the standard H_∞ formulation, and equation (27) will not be satisfied. It is worth noting that a necessary condition for satisfying equation (27) is that $F(z)P(z)$ is a minimum phase system. Due to the relative degree of $P(z)$ is greater than zero, $F(z)$ should be a non-causal controller for equation (27) to be satisfied. As the previous pass seam boundary error is known and the repetitive disturbance can be predicted for the entire pass, a non-causal controller $F(z)$ can be implemented. Utilizing a

10 similar methodology in [6], $\|S(z)G(z)\|_\infty$ can be derived as

$$\begin{aligned} \|S(z)G(z)\|_\infty &= \|S(z)z^{-q}G(z)\|_\infty \\ &= \left\| S(z) \frac{z^{-q} - \tilde{F}(z)P(z)}{1 + C(z)P(z)} \right\|_\infty \end{aligned} \quad \text{--equation (28)}$$

where $\tilde{F}(z) = z^{-q}F(z)$ and $q \in \mathbb{Z}^+$.

As such, solving for the inequality in (27) can be regarded as finding a $\tilde{F}(z)$ such that

$$\left\| S(z) \frac{z^{-q} - \tilde{F}(z)P(z)}{1 + C(z)P(z)} \right\|_\infty < 1. \quad \text{--equation (29)}$$

20

Solving for the inequality in equation (19) is a standard H_∞ loop shaping problem, which can be solved using the LMI (linear matrix inequality) approach in MATLAB, also detailed in [22]. After designing a causal filter $\tilde{F}(z)$, the corresponding non-causal feedforward controller can be obtained as $F(z) = z^q \tilde{F}(z)$.

25

Embodiments of the invention provide several advantages including, but not limited to, the following:

- In particular, the invention achieves or allows half-overlapping between two adjacent welding passes, weld seam tracking, weld pool monitoring, irregularity compensation, desired filling profile, adjustable torch travelling speed, and compensation from both repetitive and non-repetitive disturbances. It will be appreciated from Table 3 that while conventional offline planning-based filling and online tracking-based filling would be able to achieve some of these listed capabilities, the invention is capable of achieving a full spectrum of the listed capabilities.

Table 3

Capability		Offline Planning- Based Filling	Online Tracking- Based Filling	Invention
1	Half-Overlapping between adjacent welding passes	NO	YES	YES
2	Weld Seam Tracking	NO	YES	YES
3	Weld Pool Monitoring	NO	NO	YES
4	Desired Filling Profile	YES	NO	YES
5	Adjustable Torch Traveling Speed	NO	NO	YES
6	Compensating both Repetitive and Non-Repetitive Disturbances	NO	NO	YES

- Multi-pass welding can be completed with good quality and aesthetics
- Robust when environmental disturbances or system uncertainties occur as it can compensate error, the filling profile can be finished with increased accuracy

- Experimental results show that the filling profile using the proposed PC-FIA method achieves 60% decrease of RMSE with respect to the planned reference, as compared to the case of without using the proposed PC-FIA method. In addition, the allocated weaving parameters ensure that the welding inputs are always maintained within the polyhedral constraint and the whole welding quality is acceptable by industry standard.

Other embodiments will be apparent to those skilled in the art from consideration of the specification and practice of the invention. Furthermore, certain terminology has been used for the purposes of descriptive clarity, and not to limit the disclosed embodiments of the invention.

REFERENCES

- [1] H. P. M. Yupiter, R. N. Lidam, R. M. Ridzwan, Z. M. Yusof, R. M. Ridhwan, S. M. Shahar, T. Ghalib, and K. A. Sunhaji, "Welding distortion analysis of multipass joint combination with different sequences using 3D FEM and experiment," *International Journal of Pressure Vessels and Piping*, Vol. 111, pp. 89–98, 2013.
- [2] C. S. Pathak, L. G. Navale, A. D. Sahasrabudhe, and M. J. Rathod, "Analysis of thermal cycle during multipass arc welding," *Welding Journal*, Vol. 91, pp. 149s–154s, 2012.
- [3] C. Chen, S. Hu, D. He, and J. Shen, "An approach to the path planning of tube–sphere intersection welds with the robot dedicated to J-groove joints," *Robotics and Computer-Integrated Manufacturing*, Vol. 29, No. 4, pp. 41–48, 2013.
- [4] H. S. Moon and R. J. Beattie, "Development of adaptive fill control for multitorch multipass submerged arc welding," *The International Journal of Advanced Manufacturing Technology*, Vol. 19, No. 12, pp. 867–872, 2002.
- [5] S. Xia, Y. Z. Tan, C. K. Pang, and C. M. Chew, "Design of feedforward filling control for joining thick materials using robotic welding systems," in *Proceedings of the 14th IEEE International Workshop on Advanced Motion Control*, Auckland, New Zealand, Apr. 2016.
- [6] L. Zaccarian, "Dynamic allocation for input redundant control systems," *Automatica*, Vol. 45, pp. 1431–1438, 2009.
- [7] T.A. Johansen and T.I. Fossen, "Control allocation—a survey," *Automatica*, Vol. 49, pp. 1087–1103, 2013.

- [8] S. Xia, C. K. Pang, A. Mamun, C. M. Chew, K. P. Tan, "Feedforward compensation for suppression of seam boundary error propagation in robotic welding systems," *IEEE/ASME Transactions on Mechatronics*, Submitted.
- [9] K. Alex, C. T. Michael, L. Huang, "Large-margin convex polytope machine," in *Proceedings of Advances in NIPS*, Dec. 2014, pp. 3611–3616.
- [10] Z. Wang, N. Djuric, K. Crammer, S. Vucetic, "Trading representability for scalability: adaptive multi-hyperplane machine for nonlinear classification," in *Proceedings of the 17th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, Aug. 2011, pp. 24–32.
- [11] N. Manwani, P. S. Sastry, "Polyceptron: a polyhedral learning algorithm," *arXiv: 1107.1564*, 2013.
- [12] D. Bertsimas, O. Nohadani, K. M. Teo, "Robust optimization for unconstrained simulation-based problems," *Operations Research*, Vol. 58, No. 1, pp. 161–178, 2010.
- [13] H. D. Sherali, J. Desai, T. S. Glickman, "Optimal allocation of risk reduction resources in event trees," *Management Science*, Vol. 54, No. 7, pp. 1313–1321, 2008.
- [14] M. Tawarmalani, N. V. Sahinidis, "A polyhedral branch-and-cut approach to global optimization," *Mathematical Programming*, Vol. 103, No. 2, pp. 225–249, 2005.
- [15] D. Bertsimas, A. Thiele, "Robust and data-driven optimization: modern decision-making under uncertainty," *Tutorials on Operations Research*, INFORMS, Chapter 4, pp. 195–222, 2006.
- [16] J. Mathew, C. K. Pang, M. Luo, W. H. Leong, "Classification of imbalanced data by oversampling in kernel space of support vector machines," *IEEE Transactions on Neural Networks and Learning Systems*, in press.
- [17] H. C. Fang, S. K. Ong, A. Y. C. Nee, "Adaptive pass planning and optimization for robotic welding of complex joints," *Advances in Manufacturing*, Vol. 5, No. 2, pp. 93–104, 2017.
- [18] J. F. Hu, J. G. Yang, H. Y. Fang, G. M. Li, Y. Zhang, "Numerical simulation on temperature and stress fields of welding with weaving," *Science and Technology of Welding and Joining*, Vol. 11, No. 3, pp. 358–365, 2006.
- [19] Y. Chen, Y. He, H. Chen, H. Zhang, S. Chen, "Effect of weave frequency and amplitude on temperature field in weaving welding process," *International Journal of Advanced Manufacturing Technology*, Vol. 75, No. 5–8, pp. 803–813, 2014.
- [20] Clifford A. Mankenberg, "Tubular TYK Fabrication and Inspection," *Inspection Trends*, pp. 23–27, Fall 2004.

[21] J. B. Song and D. E. Hardt, "Dynamic modeling and adaptive control of the gas metal arc welding process," *Journal of Dynamic Systems, Measurement, and Control*, Vol. 116, No. 3, pp. 405–413, 1994.

[22] C. Doulamanidis and Y. M. Kwak, "Multivariable adaptive control of the bead profile geometry in gas metal arc welding with thermal scanning," *International Journal of Pressure Vessels and Piping*, Vol. 79, No. 4, pp. 251–262, 2002.

[23] Y. M. Zhang, R. Kovacevic, and L. Li, "Adaptive control of full penetration gas tungsten arc welding," *IEEE Transactions on Control System Technology*, Vol. 4, No. 4, pp. 394–403, July, 1996.

[24] <http://www.meta-mvs.com/vistaweld>

CLAIMS

1. A method of robotic multi-pass welding on a complex weld geometry by a welding torch, the method comprising:

5 (a) ascertaining a feedforward controller function;

(b) using machine learning training of a plurality of welding input vectors, ascertaining a plurality of desirable welding input vectors therefrom, each of the plurality of welding input vectors having parameters which include inverse travelling speed of the welding torch, weaving width of the welding torch, and weaving length of the welding torch;

10 (c) ascertaining a current inverse travelling speed of welding torch for a current pass based on at least a position error and the feedforward controller function;

(d) ascertaining an optimized welding input vector from the plurality of desirable welding input vectors wherein the optimized welding input vector includes the current inverse travelling speed; and

15 (e) performing robotic welding based on parameters of the optimized welding input vector,

wherein step (a) includes ascertaining the feedforward controller function F based on a H-infinity (H_∞) controller which satisfies a minimisation problem as follows

$$\begin{aligned} \min_F \quad & \left\| \frac{1}{FP} \right\|_\infty \\ \text{s.t.} \quad & \|1 - FP\|_\infty < 1 \end{aligned}$$

20 wherein P is a low order and linear time invariant (LTI) model.

2. The method of claim 1, wherein the position error is ascertained based on a difference between a reference welding profile of a previous layer and the actual welding profile of the previous layer.

25 3. The method of claim 2, wherein the reference welding profile is ascertained based on the weld geometry and a count of planned layers of weld.

4. The method of claim 1, wherein after performing robotic welding, the method further
30 comprising:

upon ascertaining a current layer is complete, detecting an actual welding profile of the current layer for ascertaining a next position error for a next layer subsequent to the current layer; and

repeating steps (c), (d) and (e) for the next layer.

5

5. The method of claim 1, wherein after performing robotic welding, the method further comprising:

upon ascertaining a current layer is incomplete, repeating steps (c), (d) and (e).

10 6. The method of any one of claims 1 to 5, wherein step (b) includes using a polyhedral machine learning algorithm for machine learning training of the plurality of welding input vectors.

15 7. The method of any one of claims 1 to 6, wherein step (c) includes ascertaining the current inverse travelling speed of welding torch for a current pass based on

$$v^{-1}(k) = e^{l-1}(k)F + v_c^{-1}(0)$$

wherein $v^{-1}(k)$ is the current inverse travelling speed at time sample k, $e^{l-1}(k)$ is the position error, F is the feedforward controller function, and $v_c^{-1}(0)$ is a constant.

20 8. A robotic welding system for performing multi-pass welding on a complex welding geometry, the system comprising:

a welding torch and a robot manipulator supporting the welding torch;

at least one sensor;

a computing unit communicably coupled to the robot manipulator and the sensor;

25 a memory storage communicably coupled to the computing unit and includes computer-executable instructions to:

(a) ascertain a feedforward controller function;

30 (b) using machine learning training of a plurality of welding input vectors, ascertain a plurality of desirable welding input vectors therefrom, each of the plurality of welding input vectors having parameters which include inverse travelling speed of the welding torch, weaving width of the welding torch, and weaving length of the welding torch;

(c) ascertain a current inverse travelling speed of welding torch for a current pass based on at least a position error and the feedforward controller function; and

(d) ascertain an optimized welding input vector from the plurality of desirable welding input vectors wherein the optimized welding input vector includes the current inverse travelling speed;

(e) control the welding torch and robotic manipulator to perform robotic welding based on parameters of the optimized welding input vector,

wherein the memory storage further includes computer-executable instructions to, in step (a), to ascertain the feedforward controller function F based on a H-infinity (H_∞) controller which satisfies a minimisation problem as follows

$$\begin{aligned} \min_F \quad & \left\| \frac{1}{FP} \right\|_\infty \\ \text{s.t.} \quad & \|1 - FP\|_\infty < 1 \end{aligned}$$

wherein P is a low order and linear time invariant (LTI) model.

9. The robotic welding system of claim 8, wherein the memory storage further includes computer-executable instructions to ascertain position error based on a difference between a reference welding profile of a previous layer and the actual welding profile of the previous layer.

10. The robotic welding system of claim 9, wherein the reference welding profile is ascertained based on the weld geometry and a count of planned layers of weld.

11. The robotic welding system of claim 8, wherein the memory storage further includes computer-executable instructions to

after performing robotic welding and upon ascertaining a current layer is complete, detect an actual welding profile of the current layer for ascertaining a next position error for a next layer subsequent to the current layer; and

repeat steps (c), (d) and (e) for the next layer.

12. The robotic welding system of claim 8, wherein the memory storage further includes computer-executable instructions to

after performing robotic welding and upon ascertaining a current layer is incomplete, repeating steps (c), (d) and (e).

13. The robotic welding system of any one of claims 8 to 12, wherein the memory storage
5 further includes computer-executable instructions to, in step (b), use a polyhedral machine learning algorithm for machine learning training of the plurality of welding input vectors.

14. The robotic welding system of any one of claims 8 to 13, wherein the memory storage
10 further includes computer-executable instructions to, in step (c), ascertain the current inverse travelling speed of welding torch for a current pass based on

$$v^{-1}(k) = e^{l-1}(k)F + v_c^{-1}(0)$$

wherein $v^{-1}(k)$ is the current inverse travelling speed at time sample k, $e^{l-1}(k)$ is the position error, F is the feedforward controller function, and $v_c^{-1}(0)$ is a constant.

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