Sensing of the Weld Pool Depth with Neural Network and Fuzzy Control of Seam Tracking

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Abstract – This paper deals with the problem concerning the sensing of the weld pool and the tracking of the welding line with welding robots. In order to obtain a good quality of the welding result, it is important to control the weld pool depth and to keep the torch posture constant regardless of the external disturbance.First, a new method proposed for sensing the weld pool depth with the neural network. The depth is kept constant regardless of the disturbance, such as the variation of the groove gap, with the fuzzy controller. Next, the method of the seam tracking is discussed, when the pipe is joined to the plane. The CCD camera and the laser are used to detect the welding line and to control the torch posture. The torch axis ϕ of the robot, its root axis θ, and the torch height are controlled with the fuzzy controller. The validity of the neural network and the fuzzy controller is verified by performing the experiments.

INTRODUCTION

In general, the teaching playback are used to the control of industrial robots. Since the robots are operated according to the preset database, the feed back of the state was not performed. When the data is differed from the present state by the disturbance and so on, the good quality of the result may be not obtained. It is important to construct the robots with the feedback of the state. This paper deals with the problem to realize the intelligence to the welding robot. The problem included two parts. One is the sensing and controlling of the weld pool. Another is the tracking of the welding line.

First, the weld pool depth in the joining part is one of factors to determine the mechanical strength. It is important to keep the weld pool depth constant. In general, it is difficult to directly observe the weld pool depth with a TV camera. Moreover, since the welding phenomena are described by partial differential equations, it is difficult to construct the depth's mathematical model described by state equations[1,2]. A new method is proposed for measuring the weld pool depth. In the method, the weld pool depth is estimated by using the information obtained from the welding side, i.e. the depth of the weld pool is estimated from the surface shapes of the weld pool, the state of the heat input, which corresponds to the changes of the welding current, and the state of the groove gap.

Next, the method of the seam tracking, when the pipe is joined to the plane, is proposed. The motion equation is complicated, since the robots has 5 axis and the moment of inertia is changing according to the torch position. One of the advantage of the fuzzy controller is easy to describe the expert knowledge[3]. The fuzzy controller is valid for the plant, of which the construction of the mathematical model may be difficult. Therefore, the seam tracking is controlled with the fuzzy controller. The validity of the neural network and the fuzzy controller are verified by the experiments.

NEURAL NETWORK TO DESCRIBE THE DYNAMICAL SYSTEM OF THE WELD POOL DEPTH

Since it is difficult to directly measure the weld pool depth during the welding, the neural network is used to describe the weld pool depth. The relationship among the molten metal, the groove gap, and the base metal is illustrated in Fig.1. When the base metal melts to the back side, the back bead generates. The width of the back bead becomes wide when the weld pool depth becomes deep. The typical image of the weld pool surface is shown in Fig.2 with the CCD camera. The width W_0 at just under the electrode and the width W_1 at 4.17mm behind the electrode are measured by processing the image.

The dominant factors of the weld pool depth are discussed to find the input of the neural network. The fundamental experiments are performed in the following condition : the thickness of the base metal is the mild steel of 3.2mm thickness, the welding speed is 25 cm/min, the range of the current is from 90 to 140 A, the two base metals are joined without the groove gap. The relationship among the surface shape of the weld pool, the weld pool depth, the welding current is shown in Fig.3. From the result the relationship between the surface shape of the pool and weld pool depth is

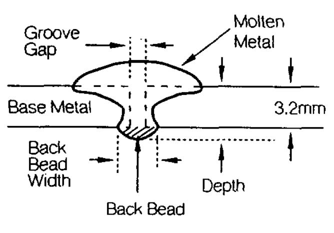

Fig.1 Conception figure of the weld pool.

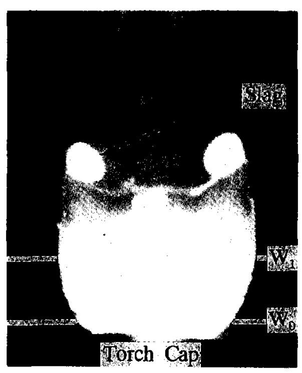

Fig.2 Typical image of the weld pool after processing.

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discussed. The heat input to the base metal becomes big when the welding current increases. The surface shape of the weld pool becomes large when the weld pool depth is below about 4.5mm and the heat input increases. When the depth is over 4.5mm and the heat input increase slightly, the much molten metal appears to the back side. Hence the area of the surface shape becomes small.

The fundamental experiments with the groove gap of 1mm is performed in the same conditions as that without the groove gap. The relationship among the surface shape of the weld pool, the weld pool depth, the welding current is shown in Fig.4. The relationship among the surface shape of the weld pool, the width of the groove gap, and the weld pool depth is discussed. The weld pool depth becomes deep as the heat input increases. When the heat input is the same as the case without the groove gap, the weld pool depth of the case with the groove gap of 1 mm is deeper than that without the groove gap, because the molten metals enter into the groove gap, when the groove gap becomes wide. The weld pool depth becomes deep as the width of the groove gap increases. The variation of the welding current, the groove gap, and the variation of the surface shape are used to describe the dynamical system of the weld pool depth. The three layer feedforward neural network is constructed to describe the dynamical system of the weld pool depth as shown in Fig.5.

The information used to the input layer is illustrated in Fig.6. The width of the groove gap at the position of sensing the pool width can not directly measured, since the molten metal fills the groove gap. The width G_{k+90} of the groove gap at 25mm before the electrode, where k is the number of sampling, is measured. The width G_{k+90} is stored into the memory of the

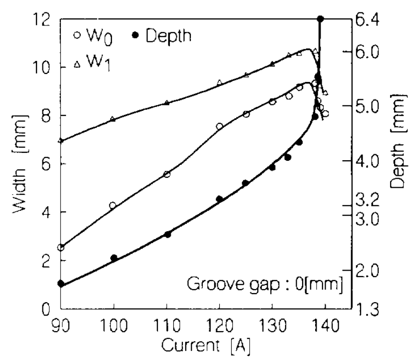

Fig.3 Relationship among the width, the depth, and the current in the steady state without the groove gap.

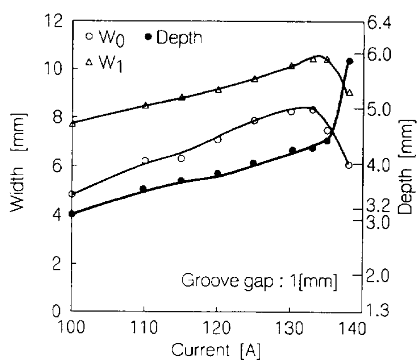

Fig.4 Relationship among the width, the depth, and the current in the steady state with the groove gap of 1mm.

personal computer. The width G_k of the groove gap just under the electrode is obtained by using the stored width of the groove gap. The width of the groove gap at the sensing point W_0 and W_1 correspond to G_k and G_{k-15}, respectively.

The variation of surface shape of the pool is detected by examining the variation of the front part of the surface shape. So that the variation of the width W_0 and W_1 in 1s is adapted as the information of the variation of the surface shape, i.e. the values of the width W_0 and W_1 per 2 sampling periods are given to the neural network : $W_{0,k}$, $W_{0,k-2}$, $\cdots$, $W_{0,k-14}$, $W_{1,k}$, $\cdots$ $W_{1,k-14}$, where k is sampling iteration and the sampling period is 4/60s. Similarly, the variation of the welding current and of the groove gap : i_k, i_{k-2}, $\cdots$ i_{k-14}, G_k, G_{k-2}, $\cdots$ G_{k-14}, G_{k-15}, G_{k-17}, $\cdots$ G_{k-29}. The input layer is constructed from 40 units.

Training of neural network

The neural network is trained by using back propagation method. The training data are constructed from the relationship among the surface shape

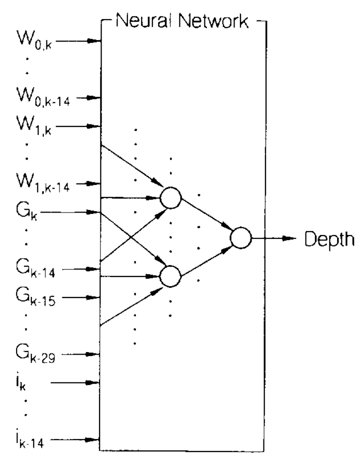

Fig.5 Three layer neural network to describe the weld pool depth.

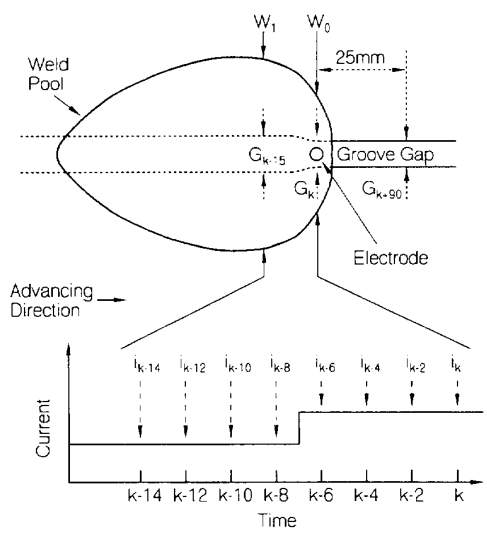

Fig.6 Input variables to the neural network.

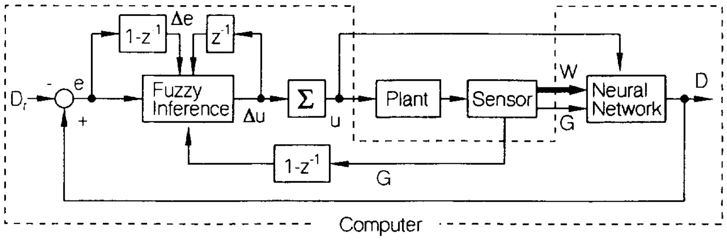

Fig.7 Neuro-fuzzy controller of controlling the weld pool depth.

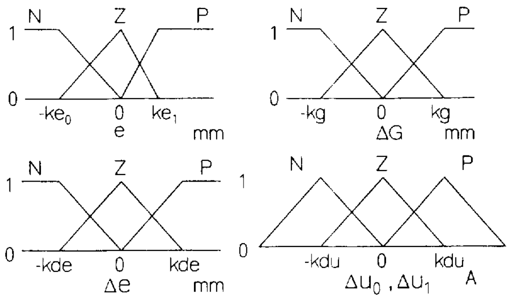

Fig.8 Fuzzy variables.

Table 1 Rules for the weld pool depth control.

Δe \ e	N	Z	P
P	Z	N	N
Z	P	Z	N
N	P	P	Z

→ Δu_0

P=Positive
Z=Zero
N=Negative

ΔG	N	Z	P
Δu_1	P	Z	N

$$\Delta u[n]=\Delta u_0 + \Delta u_1 - 0.4\Delta u[n-1]$$

of the weld pool, the welding current, and the weld pool depth in the steady state and the transient state. From the fundamental experiments, the weld pool depth of 6.4mm, which is two times of the base metal's thickness, corresponds to the case in which the base metal is through down. Therefore, let the output of the neural network be from 0mm to 6.4mm.

The number of units at the hidden layer is decreased while the training error becomes below 3%. The resultant number of the units in the hidden layer is 11.

Design of fuzzy controllers

The block diagram of controlling the weld pool depth is shown in Fig.7. Let the desired weld pool depth be D_r. The neural network procedures the weld pool depth D. The deviation e (= D − D_r) is calculated from the output of the neural network. The weld pool depth changes by the variation of the width of the groove gap. Since the width before the electrode is taken with the CCD camera 2, the width of the groove gap just under the electrode is already given. In order to control the weld pool depth without the time delay, the feedforward control system is constructed for the variation of the groove gap's width. On the other hand, the feedback control system for the weld pool depth includes the time delay of one sampling

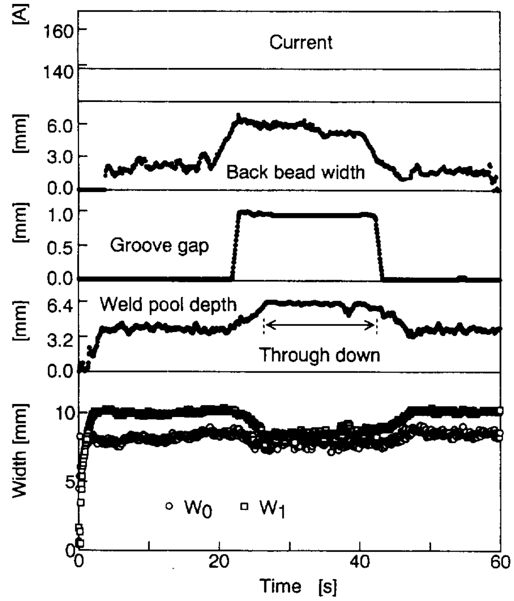

Fig.9 Experimental result with the constant current.

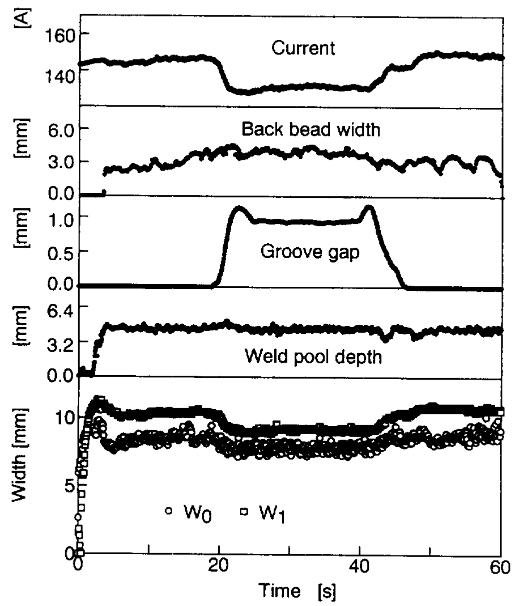

Fig.10 Experimental result with the fuzzy controller.

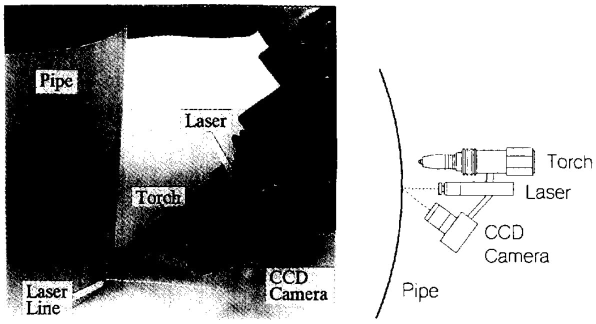

Fig.11 The relationship between the torch and the pipe.

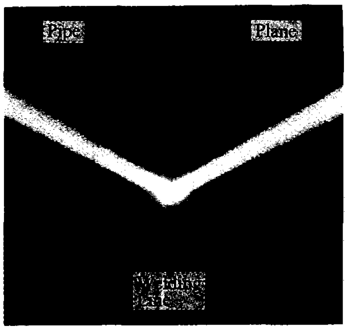

Fig.12 Typical image of the light.

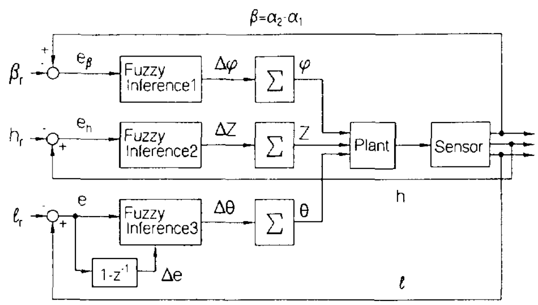

Fig.13 Fuzzy controller for the seam tracking.

period, which needs to process the image and to determine the welding current. The control block diagram is constructed from the feedforward system and feedback system. The fuzzy variables and the control rules of the fuzzy controller are shown in Fig.8 and Table 1. The manipulating variable $\Delta u[n]$ is inferred from the deviation $e[n]$, it's variation $\Delta e[n]$, the prior manipulating variable $\Delta u[n-1]$, and the variation $\Delta G[n]$ of the groove gap.

EXPERIMENTAL RESULTS OFF THE POOL DEPTH CONTROL

The welding experiment is performed to verify the performance of the fuzzy controller. The base metal is the same as that used in the fundamental experiments. The welding conditions are as follows:

1) The base metal is the mild steel SS41 of 3.2 mm thickness.
2) The welding speed is 25 cm/min.
3) The shielding gas is the mixing of Ar 98 % and O_2 2%.
4) The reference of the depth is 4.5mm.
5) The width of the groove gap is changed from 0mm to 1.0mm as the disturbance.

First, the welding experiment is performed by using the constant welding current of 138A. The variation of the groove gap's width, the response of the surface shape of the weld pool, and the change of the welding current are shown in Fig.9. The weld pool depth is the output of the neural network. When the width of the groove gap is wide, the base metal burn through.

Next, the welding experiment with the fuzzy controller is performed by using the same welding condition as the case of the constant welding current. Let ke_0, ke_1, kde, kdu for Δu_0, kg, and kdu for Δu_1 be 2.5, 1.3, 0.5, 1.0, 1.0, and 20, respectively. The welding result with the fuzzy controller is shown in Fig.10. The good performance is obtained, since the weld pool depth measured after the welding is about uniform. Moreover, when the width of the groove gap becomes wide, the welding current is decreasing as shown in Fig.10. On the other hand, when the width of the groove gap becomes narrow, the welding current is increasing.

SYSTEM OF DETECTING THE WELDING LINE

A CCD camera and a laser which are used to detect the welding line ,and are ahead of the torch of the arm type robot, as shown in Fig.11. The light is emitted from the laser to the plane vertically.The light on the plane and the pipe is taken with the CCD camera.Its typical image are shown in Fig.12 when the torch posture is 45° against the plane.The personal computer detects the torch posture and the welding line by processing *V* from the image and infers the advancing direction of the torch to trace the welding line and to control the torch posture by the fuzzy logic. The number of the pulse is calculated to move the axes of the robot and is sent to the robot from the computer.

DESIGN OF THE FUZZY CONTROLLER BASED ON THE KNOWLEDGE

The torch height, the ϕ axis, and the θ axis are controlled with fuzzy controller shown in Fig.13. The performance of the fuzzy controller depends on the fuzzy variables and the rules. The control rules are designed from the operator's knowledge.

First,the rules are discussed for controlling the angle of θ axis.The cross point of the right line and the left line which construct the *V* form is located on the center of the monitor when the torch is inclined to 45°,as illustrated in Fig.14(a). The *V* form is symmetric to vertical line at the center of the monitor. Therefore, the angle α_1,which corresponds to the incline from the horizontal line, is equal to the angle α_2. When the distance between the top of the torch and the welding line is not changed and the torch axis ϕ is over 45°, the *V* form inclines left on the monitor as shown if Fig.14(b). Then α_1 is smaller than α_2. On the other hand,when the axis ϕ is below 45°, the *V* form inclines right on the monitor as shown in Fig.14(c). The control rules for the torch posture are constructed from the relationship between its posture and the *V* form.For example, if the *V* form inclines left,i.e., $\beta=\alpha_2-\alpha_1$ is positive,the torch posture approaches 45° by decreasing the angle of the axis ϕ. This can be described by if–then form:

If β is Positive then $\Delta\phi$ is Negative. (1)

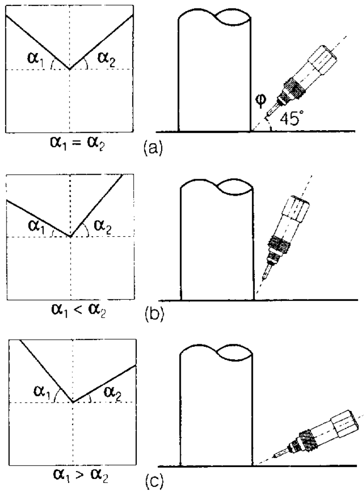

Fig.14 The control of the ϕ axis of the robot.

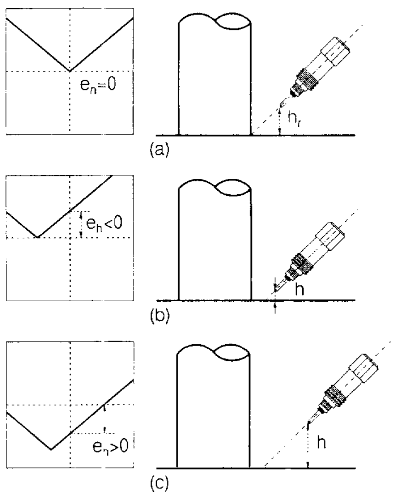

Fig.15 The control of the torch height.

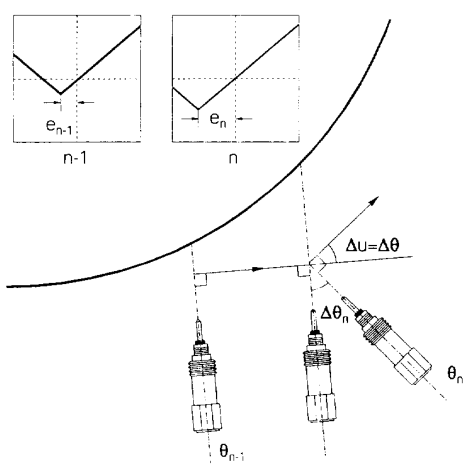

Fig.16 The control of the θ axis.

Table 2 Control rules for the ϕ axis, the θ axis, and the torch height.

Δe \ e	N	Z	P
P	Z	N	N
Z	P	Z	N
N	P	P	Z

$\leftarrow \Delta\theta$

β	N	Z	P
$\Delta\phi$	P	Z	N

e_h	N	Z	P
ΔZ	P	Z	N

P = Positive
Z = Zero
N = Negative

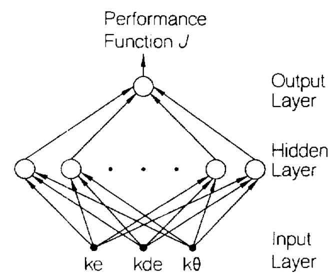

Fig.17 Neural network to find the performance function.

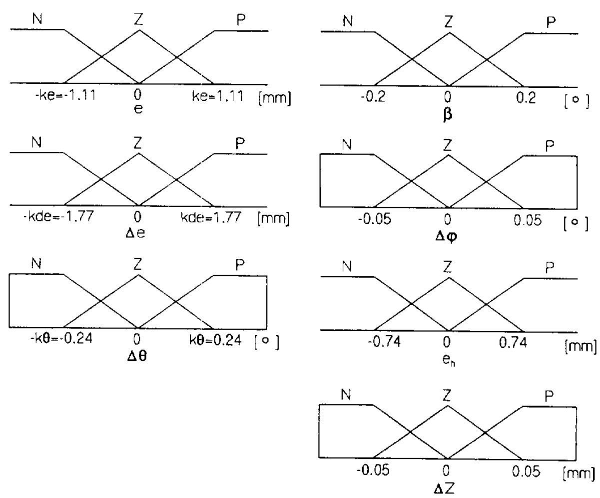

Fig.18 Fuzzy variables for the seam tracking.

where $\Delta\phi$ is the variation of the axis ϕ.The control rules shown in Table 2 are constructed from the above mentioned.

Next,the method of controlling the torch height is discussed.Suppose the torch height is *hr* and the *V* form is located to the center on the monitor, as shown in Fig.15(a). If the height becomes lower than *hr*, the cross point of

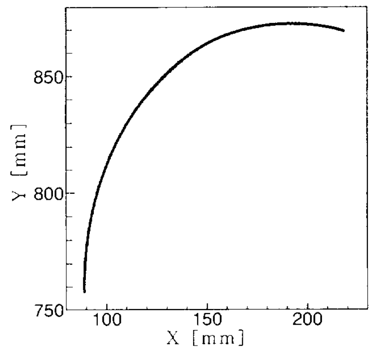

Fig.19 Tracking result.

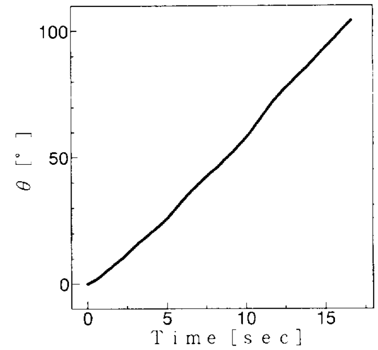

Fig.20 Experimental result of the θ axis control.

the *V* form moves down and *eh* becomes negative. On the other hand,if the torch height becomes higher than *hr*, the cross point moves up and *eh* becomes positive. The control rules for the torch height are constructed from the mentioned knowledge. For example, if the torch height is higher than *hr*, the torch height should be decreased.This is written by the if–then form:

If *eh* is Positive then ΔZ is Negative. (2)

where ΔZ is the variation of the torch height.

Moreover, the tracking of the welding line and the control of the θ axis are discussed. The relationship between the pipe and the torch is illustrated in Fig.16. The torch moves vertical against the axis of that and parallel against the plane under the constant speed. Suppose the present angle in the axis of the root of the torch and the prior angle are θ_n and θ_{n-1}, respectively. If the torch inclines backward against the welding line , the torch leaves the welding line and the cross point on the monitor moves left. The variation of the rotation angle of the θ axis is inferred from the deviation *e*, which corresponds to the distance between the top of the torch and the welding line, and its variation Δe. Since the torch moves along the vertical line of the axis, the rotation of the θ axis corresponds to the variation of the advancing direction . On the other hand, if the torch inclines forward against the welding line, the torch approaches the welding line and the cross point on the monitor moves right. The control rules are constructed from the mentioned knowledge. For example, if the torch leaves the welding line and is leaving the welding line, the θ had better rotate positively to approach the line. This is written by using if–then form:

If *e* is Negative and Δe is Negative then $\Delta\theta$ is Positive. (3)

The control rules are shown in Table 5. The if–part is determined from the torch posture and its variation and then –part is determined from the operator's knowledge in the situation corresponded to the if–part.

Tracking Experiments

The authors perform the tracking experiments to verify the validity of the proposed method under the following conditions:

1) The diameter of the pipe is 217mm.
2) The advancing speed is 12mm/s.
3) The sampling period is 33.4 ms (1/30s).

The performance of the tracking depends on the control rules and the fuzzy variables. The performance function *J* which is summing up the square of the deviations is determined and is found for the various of the parameters of the fuzzy variables by using the neural network in Fig.17. The optimal parameters kde and kθ of the fuzzy variables is calculated by using the neural network and the steepest descent method. The control rules in Table 2 and the tuned fuzzy variables in Fig.18 are used. As shown in Fig.19, the good tracking result is obtained. The θ axis is rotating smoothly for the advance of the torch, as shown in Fig.20.

Conclusions

This paper deals with the problem concerning the intelligent welding robots. First, the sensing and the controlling of the weld pool depth is discussed. The method to measure the depth is proposed with the neural network, since the depth cannot be directly measured at real time. The weld pool depth is estimated by using the information obtained from the welding side. When the width of the groove gap changes, the weld pool depth changes, too. The feedforward control system for the variation of the groove gap's width just under the electrode can be constructed by observing the groove gap's width before the electrode. The feedback control system was constructed so as to keep the output of the neural network constant.Namely, the fuzzy control system was constructed from the feedback control part and the feedforward control part.

Next, The seam tracking and the controlling of the torch posture are discussed when the pipe is joined to the plane by using the arm type robots. A new method was proposed for tracking the welding line and controlling of the torch posture by the fuzzy inference, i.e., the advancing direction is changing by the rotation of the θ axis of the robot. The sensing of the posture and the welding line are used to the CCD camera and the laser. The validity of the fuzzy controller was verified by doing the welding experiments and the tracking experiments.

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