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Classification of Fuzzy Logic on the Optimized Bead Geometry in the Gas Metal Arc Welding

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Abstract

Recently, there has been a rapid development in computer technology, which has in turn led to develop the automated welding system using Artificial Intelligence (AI). However, the automated welding system has not been achieved duo to difficulties of the control and sensor technologies. In this paper, the classification of the optimized bead geometry such as bead width, height, penetration and bead area in the Gas Metal Arc (GMA) welding with fuzzy logic is presented. The fuzzy C-Means algorithm (FCM), which is best known an unsupervised fuzzy clustering algorithm is employed here to analysis the specimen of the bead geometry. Then the quality of the GMA welding can be classified by this fuzzy clustering technique and the choice for obtaining the optimal bead geometry can also be determined.

Key Words : Gas metal arc welding, Fuzzy c-means algorithm, Bead geometry

1. Introduction

Each welded application has different optimum process parameters such as arc current, welding voltage and welding speed in terms of the weld characteristics desired. Consequently, incorrect settings of those process parameters give rise to deviations in the welding characteristics from the desired bead geometry. Therefore, trainee welders are referred to the tabulated information relating different metal types and thickness as to recommend the desired values of process parameters. Basically, the bead geometry plays an important role in determining the mechanical properties of the weld. So it is very important to select the process parameters for obtaining optimal bead geometry. However, it is difficult for the traditional identification methods to provide an accurate model because the optimized welding process is non-linear and time-dependent(1). Modeling of phenomena for the arc welding process has been a major preoccupation over the years. For the purpose of representing the essential aspects of a specific system, the study of the relationships between process parameters and bead geometry as welding quality has

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been concentrated on nowadays. And in such a way the literature abounds with the relationships can be employed for the process optimization[2]. But traditional analysis techniques were too precise for many complex real-world problems. Therefore fuzzy logic seems to be a convenient tool to solve problems in some imprecise way. Imprecision, here means the sense of vagueness rather than the lack of knowledge about the value of a parameter. Fuzzy set theory provides a strict mathematical framework in which vague conceptual phenomena can be precisely and rigorously studied. It can also be considered as a modeling language well suited for situations in which fuzzy relations, criteria, and phenomena exist[3].

The idea of fuzzy sets was born in 1964 by Zadeh in USA. In this decade many researchers[4] around the world became Zadehs followers. Great works was accomplished and this established the foundation of fuzzy logic technology and led to the development of application of this technology. In the second decade, the first industrial application of fuzzy logic was developed by Blue Circle Cement and SIRA in Denmark[4]. The system is a cement kiln controller that incorporates the know-how of experienced operators. After being mostly viewed as a controversial technology for two decades, fuzzy logic has finally been accepted as an emerging technology since the late 1980s. This is largely due to a wide array of successful applications ranging form consumer products, to industrial process control, to automotive applications[4].

Park[5] formulated a system to perform real time evaluations of the weld quality using a fuzzy multi-feature pattern recognition with the measured signals. Tarng[6] used a fuzzy clustering technique, c-means algorithm, to classify and verify the quality of aluminum welds based on the weld pool geometry in Tungsten Inert Gas welding(TIG). Liao[7] presented a welding flaw detection methodology based on two fuzzy clustering methods, i.e. fuzzy k nearest neighbors (K-NN) and fuzzy c-means are studied and compared. Li[8] presented a novel technique, which combined both fuzzy logic control, and neural network (NN) techniques to control the Gas Tungsten Arc Welding (GTAW) process. And this technique overcomes limitations such as the dependency on the experts for fuzzy rule generation and non-adaptive fuzzy set.

In this study, a fuzzy clustering technique, c-means algorithm that was introduced in the ISODATA (Iterative Self-Organizing Data Analysis Technique) clustering method, has been applied to classify and verify the quality of the GMA welding based on the analysis of the bead geometry (bead width, height, penetration and bead area). The fuzzy c-means (FCM) generalizes the c-means algorithm to allow a point to partially belong to multiple clusterings[4]. In c-means algorithm, the data of the bead geometry can be classified into three clusterings here: good, fair and poor. Thus the classification of the bead geometry can be get. And according to the values of the membership degree of the bead geometry corresponding to different clusters good bead welding quality can also be achieved.

2. Welding Equipment and Procedure

The GMA welding process is a very complex process which involves many scientific and engineering disciplines such as chemistry, physics, metallurgy, material science and mechanics, and has been employed to join any metal using many joint configurations, and in all welding positions[9].

In this study, the experimental materials were $200 \times 70 \times 12$mm steel SS400 plates. The mechanical properties and chemical composition of base metal are shown in Tables 1 and 2. The chosen process parameters were wire diameter, arc voltage, welding speed and welding current with different values (Table 3). Also the experimental runs carried out in this study were shown in Table 3. Each process parameter is assigned to a column, sixteen process parameter combinations being available. And each row corresponds to one experimental run.

Table 1 Mechanical properties of base metal

Material	Tensile strength (kg/㎟)	Yield point (kg/㎟)	Elongation (%)	Impact value (kgm/㎠)	Hardness (Hv)
SS400	43.5	32.5	25	6.2	128

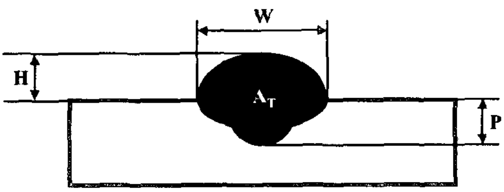
Table 2 Chemical composition of base metal

Element (%)	C	Si	Mn	P	S	Cu	Cr	Ni	Fe
SS400	0.15	0.0	0.697	0.013	0.007	0.041	0.087	0.503	Bal.

Table 3 Process parameters and their values

Number of the trial	Process parameter			
	Wire diameter (mm)	Arc voltage (V)	Welding speed (cm/min)	Welding current (A)
1	1.2	20	25	360
2	1.2	20	41	180
3	1.2	20	41	360
4	1.2	25	25	260
5	1.2	30	25	180
6	1.2	30	25	360
7	1.2	30	41	180
8	1.2	30	41	360
9	1.6	25	41	260
10	1.6	20	25	360
11	1.6	20	41	180
12	1.6	20	41	360
13	1.6	30	25	180
14	1.6	30	25	360
15	1.6	30	41	180
16	1.6	30	41	360

When it comes to measure the bead geometry, the bead section was cut transversely from the middle position using wire cutting machine. The incised plane was the specimen and it should be polished. In order to assure the precision of the specimen dimension it was etched by HNO_3 3% and H_2O 97% nital solution. To evaluate the quality of GAM welding, the measurements of the bead geometry were performed. The schematic diagram of bead geometry was shown in *Fig. 1*.



W: Bead width H : Bead height
P : Bead penetration A_T: Bead area

Fig. 1 Dimension of bead geometry for the study

The bead width (W), bead height (H), bead penetration (P) and bead area (A_T) are employed to describe the bead geometry. Basically, bead penetration must be achieved to ensure the weld strength. The bead width, bead height, bead penetration and bead area, therefore, have a lower-the-better quality characteristic(6).

The welding facility at the Welding and Intelligent Control Lab in Mokpo National University was chosen as the basis of the data collection and evaluation. In the process of the experiments the Daewoo ABB1500 robot manipulator was used to control the welding and a GMA welding unit was also employed in the experiment work. With the welder and argon shield gas turned on, the robot was initialized and welding was then executed.

3. Experimental results and classification

The experimental results for the bead geometry are shown in Table 4. As discussed earlier, the quality characteristics, bead width, bead height, bead penetration and bead area are lower-the-better ones. But the degree of the lower is a vague conception. The fuzzy logic has been proved to be useful for dealing with this kind of ambiguous problem proposed above[10].

Table 4 Experimental results for the bead geometry

No	Bead width (mm)	Bead height (mm)	Bead penetration (mm)	Bead area (mm)
1	13.71	5.39	6.68	62.60
2	8.08	2.75	1.84	19.40
3	10.30	4.64	4.13	40.58
4	13.04	3.49	3.43	52.78
5	14.20	2.09	2.12	35.24
6	15.36	2.64	6.25	83.98
7	10.91	2.20	1.81	24.84
8	14.10	2.95	5.81	50.74
9	11.94	2.4	2.41	41.81
10	14.26	4.87	3.85	61.06
11	8.94	2.24	1.75	21.00
12	12.35	4.18	3.82	49.86
13	16.20	2.51	2.00	41.24
14	20.06	3.51	5.37	86.15
15	12.55	2.32	1.14	31.38
16	16.83	4.93	5.14	61.96

3.1 Fuzzy c-means algorithm

Fuzzy c-means(FCM) algorithm presented by Bezdek [11] allows all samples belong to a certain clustering but all with a different membership. The detailed algorithm is given as follows.

Let the data set $X=\{x_1,\cdots,x_n\}\subseteq R^p$ be a subset of the real p-dimensional vector space R^p. Each $x_k=(x_{k1,}\cdots,x_{kp})\subseteq R^p$ is call a feature vector. x_{kj} is the jth feature of observation x_k and $k=1,2,\cdots,n$. Each partition of the data set $X=\{x_1,\cdots,x_n\}$ into fuzzy subsets $\mathfrak{S}_i$ $(i=1,\cdots c)$ can fully be described by a membership function $\mu_{\mathfrak{S}_i}$. That is

$$\mu_{\mathfrak{S}_i}:X\rightarrow[0,1] \tag{1}$$

Such that c, an integer $(2\le c<n)$, is the number of the fuzzy subsets $\mathfrak{S}_i$.

Let V_{cn} is the set of all real $c\times n$ matrices. $U=[\mu_{ik}]\in V_{cn}$ is called a fuzzy- c partition of the data set X if it satisfies the following conditions:

$$1.\ \mu_{ik}\in[0,1] \qquad 1\le i\le c,\ 1\le k\le n \tag{2}$$

$$2.\ \sum_{i=1}^{c}\mu_{ik}=1, \qquad 1\le k\le n \tag{3}$$

$$3.\ 0<\sum_{i=1}^{c}\mu_{ik}<n \qquad 1\le i\le c \tag{4}$$

The set of all matrices that satisfy these conditons is called M_{cf}.

Let $v=(v_{1,}\cdots,v_c)\in R^{cp}$ $(i=1,\cdots,c)$ be the vector of all cluster centers, where the v_i in general do not correspond to elements X. One of the frequently used criteria to improve an initial partition is the so called variance criterion. In this paper the Euclidean distance d_{ik} was used and it can be expressed as:

$$d_{ik}=\ d(x_k,\nu_i)\ ||x_k-\nu_i|| =\left[\sum_{j=1}^{p}(x_{kj}-\nu_{ij})^2\right]^{1/2} \tag{5}$$

The variance criterion for fuzzy c-partition for $m>1$ can be written as:

$$\min z(U,\nu)=\sum_{i=1}^{c}\sum_{k=1}^{n}(\mu_{ik})^m\ ||x_k-\nu_i||^2 \tag{6}$$

$z(U,\nu)$ is a weighted least squares objective function. Obviously it must be minimized to obtain the optimum fuzzy partition. Here ν_i is the mean of the $x_k m$-weighted by their degrees of membership. That means that the x_k with high degrees of membership have a higher influence on ν_i than those with low degrees of membership. This tendency is strengthened by m. ν_i and μ_{ik} can be expressed as:

$$\nu_i = \frac{\sum_{k=1}^{n} (\mu_{ik})^m x_k}{\sum_{k=1}^{n} (\mu_{ik})^m} \qquad i = 1, \cdots c \tag{7}$$

$$\mu_{ik} = \frac{\left(\frac{1}{\|x_k - \nu_i\|^2} \right)^{1/(m-1)}}{\sum_{j=1}^{c} \left(\frac{1}{\|x_k - \nu_j\|^2} \right)^{1/(m-1)}} \qquad i = 1, \cdots, c,\ k = 1, \cdots, n \tag{8}$$

The systems described by (7) and (8) cannot be solved analytically. These exist iterative algorithms that approximate the minimum of the obhective function. The algorithm comprises the following steps:

Step 1. Choose $c(2 \le c < n)$, $m(1 < m < \infty)$. Initalize $U^{(0)} \in M_{fc}$, set $l = 0$.

Step 2. Calculate the c fuzzy cluster centers $\{\nu_i^{(l)}\}$ by using $U^{(l)}$ from the formulateion (7).

Step 3. Caculate the new membership matrix $U^{(l+l)}$ by using $\{\nu_i^{(l)}\}$ from the formulation (8).

Step 4. Choose a suitable matrix norm and caculate $\Delta = \|U^{(l+1)} - U^{(l)}\|$. If $\Delta > \varepsilon$, set $l = l + 1$ and go to step 2. If $\Delta < \varepsilon$ then stop and the clustering centers ν are obtained.

3.2 Fuzzy classification of GMA welding quality

As we have already proposed before our experiment work includes 16 experiments. So the data set $X = \{x_1, x_2, \cdots, , x_{16}\}$ $(n = 16)$. There are four characteristics describing the bead geometry: bead width, bead height, bead penetration and bead area. That is each feature vector x_k comprises four components (p=4). In this paper, the quality of GMA welding is classified into 3 fuzzy subsets (c=3). That is good (G), fair (F), and poor (P). m is called exponential weight. It reduces the influence of points further away from ν_i compared to that of points close to ν_i. The larger $m > 1$ the stronger is this influence. Usually $m = 2$. Here ε was chosen to be 0.0001.

Through iterative calculation using formulation (7) and (8) the positions of these cluster centers can be get and shown in Table 5. Each quality characteristic is assigned to a column, and each row corresponds to different fuzzy subsets, good, fair and poor. Because the four quality characteristics are the smaller-the-better ones the smaller the values of each feature vector are, the better the quality is. Also by the iterative calculation the membership grades for each feature vector can be get (shown in Fig. 2). And the certain feature vector can be classified into the fuzzy subset in which the value of the membership grade is the maximum among the 3 subsets. So from Fig. 2 the bead quality of the 16 welding experiments can be easily classified and listed as in Table 6. And we can also see that experiment 7 and 15 have the best bead geometry.

Table 5 Cluster centers for fuzzy subsets good, fair and poor

	Center of cluster (mm)			
	Bead width	Bead height	Bead penetration	Bead area
Good	11.63583	2.36420	1.89433	30.55326
Fair	13.28042	3.23295	4.34922	53.79234
Poor	16.76736	4.47628	5.72484	77.21545

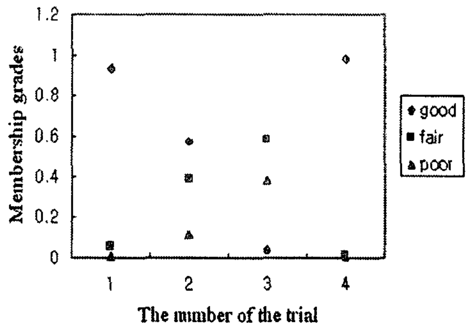


Fig. 2 Membership grades for each experimental run considering the four characteristics with the same degree of the importance

Table 6 Class of each experimental run

No.	Class	No.	Class	No.	Class	No.	Class
1	Fair	5	Good	9	Good	13	Good
2	Good	6	Poor	10	Fair	14	Poor
3	Fair	7	Good	11	Good	15	Good
4	Fair	8	Poor	12	Fair	16	Fair

The calculation proposed above according to fuzzy logic considered the four characteristics with the same degree of the importance. But in most cases the importance of the four are different because of some certain reasons. So a weighting method combined with fuzzy c-means algorithm was employed here. First, according to fuzzy c-means algorithm the grades of membership for the four quality characteristics were calculated respectively. Then here the weighting factors for the bead width and bead area are selected as 0.1,while the weighting factors of the bead height and bead penetration are selected as 0.4 based on the reasons such as the different importance or economy and so on. The grades of the membership corresponding to the overall membership are shown in Fig. 3.

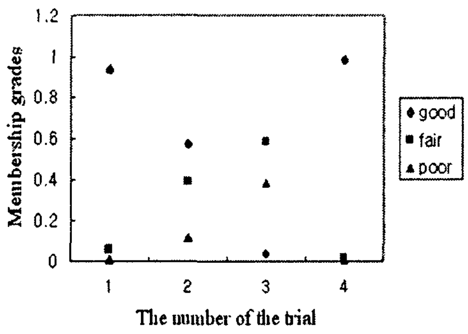


Fig. 3 Membership grades for each experimental run considering the four characteristics with different degree of the importance

Now we get the grades of membership for each experimental run calculated in different ways (shown in Fig. 2 and Fig. 3). In each figure four points were chosen to be studied which values for good quality were the maximum among the 16 experimental runs. We can see that the experiment 2, 7, 11 and 15 has the largest values of the grade of membership for good quality. And shown in Table 3 the welding speed and welding current are the same in the four experiments. The wire diameter and arc voltage can be changed freely according to the experimental condition. So the welding speed and welding current may have great effect on the quality of the bead geometry but the wire diameter and arc voltage can be determined by the experiment condition. And under the experiment condition that we have in the lab a better choice of the four process parameters for obtaining good geometry is that welding speed is chosen as 41 cm/min (chosen from 25 and 41 cm/min), welding current is chosen as 180 A (chosen from 180 to 360 A), wire diameter and arc voltage can be determined based on the experiment condition.

In order to verify the conclusions we get additional experiments were performed. The values of the four process parameters chosen for the additional experimental runs were shown in Table 7. Other experiment condition were the same as the original 16 experiments. And the experimental results for the bead geometry are shown in Table 8.

Using fuzzy logic theory the grades of the membership of the bead width, bead height, bead penetration and bead area were calculated out with the same cluster centers for fuzzy subsets good, fair and poor and were shown in Fig. 4. From Fig. 4 we can see that the grade of membership of experiment 4 for good quality is the largest one among the four experiments. It has the best bead geometry. And Table 7 shows that the welding speed and welding current chosen for experiment 4 are 41 cm/min and 180 A that are similar to the conclusions about a better choice of the four process parameters for obtaining the optimal bead geometry we get from the 16 experiments proposed above. At the same time, the experiments were also performed with changing the value of one of the two important process parameters (experiment 1 and 2) or the values of both of them (experiment 3). Seeing from Fig. 4 the grades of the membership of experiments 2 and 3 are small and the quality of the bead geometry is not good (especially experiment 3). So the welding speed and welding current have great effect on the bead geometry and the values of the two process parameters for obtaining the optimal bead geometry are 41 cm/min and 180 A.

Table 7 Process parameters and their values

Number of the trial	Process parameter			
	Wire diameter (mm)	Arc voltage (V)	Welding speed (cm/min)	Welding current (A)
1	1.2	20	25	180
2	1.2	20	41	360
3	1.6	30	25	360
4	1.6	20	41	180

Table 8 Experimental results for the bead geometry

No.	Bead width (mm)	Bead height (mm)	Bead penetration (mm)	Bead area (mm)
1	10.28	3.13	1.93	32.66
2	10.62	3.80	2.98	41.15
3	16.41	3.22	3.53	60.61
4	9.89	2.24	1.91	28.04

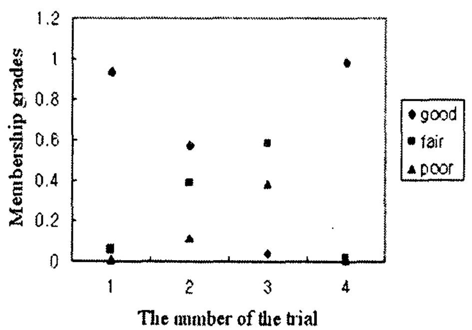


Fig. 4 Membership grades for each additional experimental run

4. Conclusions

In this paper, the classification for the bead geometry in the GMA welding with Fuzzy logic, c-means algorithm, considering multiple performance characteristics is presented. The bead geometry is based on four lower-the-better quality characteristics, that is bead width, bead height, bead penetration and bead area. By using the c-means algorithm we can classify the bead geometry into three clusters: good, fair and poor. And we can consider the four quality characteristics at the same time with the same and different degree of the importance. Thus the optimal bead geometry can be get easily according to the classification. Based on the classification of the bead geometry a better choice of the four process parameters (wire diameter, arc voltage, welding speed and welding current) in the GMA welding can also be determined. And the welding speed and welding current have great effect on the quality of the bead geometry.

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