Quality evaluation by classification of electrode force patterns in the resistance spot welding process using neural networks

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Abstract: Since resistance spot welding (RSW) has become one of the safest and most reliable processes for fabricating sheet metals, many quality estimation methods have been developed to ensure the welding qualities. In this paper, two kinds of quality evaluation method by classification of electrode force patterns using neural networks are proposed in a servo-controlled RSW system. Firstly, experiments were conducted under different welding conditions with various process parameters such as welding currents and electrode forces in order to determine the relations between force patterns and qualities. Secondly, experiments were conducted in order to generate basic data to train the proposed neural networks and finally to evaluate welding qualities through the classification into standard patterns. The proposed learning vector quantization (LVQ) net indicates the fast classification, showing a total success rate of 90 per cent for test data with five standard patterns. The proposed back-propagation (BP) net shows the precise classification with a total success rate of 95 per cent, considering a slightly longer time for classification due to the additional data process time. The results evaluated with the standard welding quality classes show the practical feasibility of the proposed classification methods.

Keywords: electrode force pattern, force slope pattern, welding quality class, learning vector quantization, back-propagation, neural network

NOTATION

- c: winner output neuron for the learning vector quantization neural network
- E: average system output error for all the sample patterns
- f: activation function
- F: electrode force
- Fs: shear strength
- Fw: welding force
- Iw: welding current
- In: indentation of nugget
- M: number of input data for the learning vector quantization net
- n: number of input neurons for an input data
- Nc: number of winner output neurons for the learning vector quantization net
- o_l: output of node i
- o_pl: output value of the output layer l for each sample p
- O_l: lth output value of output neurons for the learning vector quantization net
- O_p: output value of estimator at the output layer for each sample pattern
- P: number of input sample patterns
- S1, S2, S3: tangent values of slope 1, 2 and 3 respectively of the electrode force slope pattern
- t: time
- t_pl: target value of the output layer l for each sample p
- t_w: welding time
- W_i: weight vector connected to the lth output neuron for the learning vector quantization net
- X_i: electrode forces at the point i of 48 sampling points of forces

The MS was received on 16 December 2003 and was accepted after revision for publication on 28 June 2004.

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1 INTRODUCTION

Resistance spot welding (RSW) has been considered as an inherently safe and reliable method for joining metals and has been widely employed, especially in automobile body assembly shops. Today, most manufactures using RSW attempt to assess RSW quality by destructive methods such as a shear or peel test of weld strength or sectioning, etching and microscopic examination of nugget shape and size. As these tests are time consuming and costly, they can only be done on a sample basis, using either actual parts or simulations. Therefore, non-destructive methods to evaluate the welding qualities by monitoring process parameters such as the electrode movement and the dynamic resistance have been proposed.

After Waller and Knowlson [1] announced a measurement method of electrode separation with a gap sensor, this method has been widely used for the monitoring of welding quality. Kuchar et al. [2] reported a study on closed-loop control system by modeling the relationship between electrode separation and size of welding nugget in the RSW with stainless steels using the finite element method (FEM). Wood et al. [3] divided the pattern of electrode separation into three parameters such as the initial slope, the maximum value and the final slope of electrode separation to estimate the size of welding nugget using the non-linear least-squares fit method. After Dickinson et al. [4] proposed the variation in the dynamic resistance of the surface of both electrodes as process monitoring parameters, this method is also widely used for the effective and precise monitoring of welding quality [5–7]. The other methods using the temperature of a welding nugget [8], the ultrasound [9] and the voltage frequency of electrodes [10] were proposed for the non-destructive methods to evaluate the welding qualities by monitoring process parameters. These methods are effective for the studies in laboratories, but it is difficult to apply these methods to the RSW process in real time due to practical limitations.

Despite its seeming simplicity, RSW is a complex multi-variable process involving interaction between mechanical, electrical, thermal and material phenomena. It is very difficult to model mathematically the RSW process, because the relationship between the gun press forces changes in the press stage and the indentations of the nugget are very complex and non-linear. Therefore, the effective mapping method is required to overcome these complex and non-linear characteristics of the RSW process. The studies [11–13] using neural networks indicate that the neural network-based methods are very effective for the estimation of the welding quality, by mapping the relation between the measured process parameters and the welding quality including nugget. However, these studies have problems concerning the welding force control because they are based on the conventional RSW process with welding guns using compressed air. The studies [14–15] on the automatic spot welding using robots in automobile assembly shops proposed the RSW systems using servo-controlled welding guns driven by servos. As advantages of this servo-controlled RSW system, the welding qualities can be enhanced by controlling the welding forces, and the impact of electrodes and the spattering can be decreased by touching electrodes softly. Recent studies [16–17] proposed servo-controlled RSW systems with the variation in welding forces as process parameters for the contribution to weld qualities. However, in these studies, a quality evaluation by real-time monitoring in the RSW process with a servo-controlled gun was not performed.

The purpose of this study is to evaluate the welding quality in real time by monitoring and classifying the electrode force patterns generated from a servo-controlled gun in the RSW system. For the classification methods, the learning vector quantization (LVQ) method and the back-propagation (BP) neural network method are proposed. These classification methods are evaluated using the total success rate attained by the welding quality classes.

2 WELDING QUALITIES BY FORCE PATTERNS

2.1 RSW system using a servo-controlled welding gun

In this paper, a servo-controlled RSW system having an a.c. servo motor and a control system is presented, as illustrated in Fig. 1. The welding current and the welding time are controlled through a timer and silicon-controlled rectifier box by welding sequence control signals from a controller. The welding force is generated through the movement of ball screw connected to a servo motor by the input signals from a control system with a commercial servo driver and a controller. Then, the welding force is controlled precisely by the feedback of motor encoder signals. The welding force is measured as the electrode force processed by a signal amplifier and a digital oscilloscope with electrode force signals from strain gauges, which have been calibrated with a commercial load cell, attached to the surface of upper electrode. All the measured data including welding currents and electrode forces are managed by a personal computer system to generate and classify the standard force patterns, to train the proposed neural networks.
and to predict the types of pattern for quality evaluation. Then, the welding qualities can be highly improved by controlling not only the welding current and the welding time but also the welding force. The maximum press force of the proposed servo-controlled gun is 3000N, the maximum stroke of the electrode is 140mm and the rated output power of motor is 1.5kW. The lead of the ball screw is 10mm and the maximum speed of motor is 3000 r/min. Then, the maximum speed of the electrode is 500 mm/s.

2.2 Welding qualities according to force patterns

In the spot welding process, the measured electrode forces become a pattern as the welding progresses in real time. The pattern of electrode forces is affected by the welding current, the welding time and the welding force. Therefore, it is necessary to classify the patterns of the electrode forces into some groups in order to identify the welding quality status. Experiments were conducted under different welding conditions with various process parameters such as welding currents and electrode forces in order to obtain the best condition for good qualities. Mild thin steels with 0.8 mm thickness were used for experiments. The welding time is fixed with a value of 10 cycles, which is considered an adequate value for good welding in these experimental conditions. The welding forces are varied from 1500 to 2100N with an interval of 200N for a fixed welding current of 8kA, and the welding currents are varied from 6 to 10kA with an interval of 1 kA for a fixed welding force of 2100N. Ten samples are used for each condition. Therefore, a total of 180 data including the shear strengths and the indentations with 90 data respectively are obtained as the experimental results.

Figure 2 shows the changes in force patterns for various electrode forces from 1500 to 2100N, with a

Fig. 1 The proposed RSW system using a servo-controlled welding gun (SCR, silicon-controlled rectifier; PC, personal computer)
fixed welding current of 8 kA. In the cases of 1500 and 1700 N electrode forces, the force patterns show poor shapes with stuck welds. When the welding force is low, the local value of heat also increases as the resistance increases at the contact surfaces of thin steels. Therefore, the initial electrode forces drop due to the expulsion of inner molten materials by the large amount of heat occurring inside the two thin steels. Then, the welding quality shows weak shear strengths below 4120 N and small nugget indentations below 0.12 mm. On the other hand, in the case of 1900 N electrode forces, the force pattern shows a welding state close to the normal state. Then, the welding quality shows strong shear strengths over 4120 N, a satisfactory value of 0.8 mm for spot welding of mild steel, but the nugget indentations are large with an average value of 0.13 mm. In the case of 2100 N electrode force, the force pattern shows a good shape with smoothly rising initial electrode force curve, which represents the good inner expansion of mild steels by a proper amount of heat for good welding nugget formation. Then, the welding quality shows strong shear strengths over 4120 N and smaller nugget indentations than in the case of 1900 N electrode force.

Figure 3 shows the changes in force patterns for various welding currents from 6 to 10 kA with a fixed electrode forces of 2100 N. In the case of 6 and 7 kA welding currents, the initial electrode force patterns show the slowly rising forces due to the low welding current density. Then, the welding quality shows weak shear strengths below 4000 N and small nugget indentations below 0.1 mm, which result in stuck welding states. When the welding current is low, the local value of heat is not enough to melt the contact surfaces of thin steels for the growth of welding nuggets. In the case of 8 kA welding current, the force pattern shows a good shape with rapidly rising initial curve and a long stable middle curve during welding for good welding nugget formation.
formation. Then, the welding quality shows adequate nugget indentations around 0.125 mm and the required shear strength over 4120 N. On the other hand, in the case of 9 and 10 kA welding currents, the force patterns show poor shapes, since the forces suddenly drop during welding due to expulsion or ejection of the molten material by a large amount of heat from the high welding currents. This expulsion should be avoided since it may reduce the welding strength. Therefore, the experimental results show that the electrode force pattern indicating good welding quality with strong weld strength and small nugget indentation can be obtained in case of a welding current of 8 kA and an electrode force of 2100 N.

2.3 Classification of the standard welding quality classes

First of all, in order to evaluate the welding qualities by classification of the electrode force patterns, sample patterns classified into quality classes are required. Since the shapes of electrode force patterns are so different for the variation in the welding forces, it is better to perform the experiments with a variation in the welding currents from 6 to 10 kA with a fixed welding time of 10 cycles and welding force of 2100 N. Through the series of experiments under the welding conditions, 78 sets of sample electrode force patterns for mild thin steels with 0.8 mm thickness are collected. These sample patterns are classified into five types of standard welding quality class according to the shear strength and indentation resulting mainly from the welding currents: insufficient (I), poor (P), good (G), rich (R) and excessive (E) welding. The average values and the standard deviations of welding qualities for the five standard classes are shown in Table 1. Class 1 (I) welding state shows weak shear strength with a shallow penetration into thin steels due to insufficient heat, and class 2 (P) also shows weak shear strength with a small shallow penetration due to a small amount of heat. On the other hand, class 4 (R) and class 5 (E) show strong shear strength with a deep penetration due to the excessive heat. Finally class 3 shows strong shear strength and adequate penetration into thin steels. Therefore, the welding state with class 3 should be aimed at for the best welding quality in this RSW process. The problem to be solved next is how the measured electrode force patterns are classified successfully into the standard patterns corresponding to each welding quality class.

3 CLASSIFICATION BY LVQ NEURAL NETWORK

3.1 Pattern recognition by LVQ algorithm

The relation between the measured electrode force profiles and the standard electrode force patterns is implemented by the LVQ method, which is an unsupervised learning method for a neural network that is composed of an input layer, an output layer and a competitive layer. The LVQ method has shown good performance for complex classification problems because of their fast learning nature, reliability and convenience of use [18–20]. The LVQ neural network is a kind of winner-takes-all method, based on the competitive learning law. Figure 4 shows the LVQ algorithm proposed for a pattern classifier in this study. The 48 sampling points during the welding time of 0.48 s in which the electrode force patterns change indicate the input neurons, and the output values of output neurons become the classified standard electrode force patterns. An input datum for the jth force pattern, \( X_j \), indicates the input neurons, which can be represented as

\[
X_j = \{x_1, x_2, \ldots, x_i, \ldots, x_48\} \in R^m, \quad 1 \leq j \leq M
\]

where \( x_i \) is the electrode force at point \( i \) of the force pattern with 48 sampling points and \( M \) is the number of input sample patterns.

The output neurons indicating force patterns are fully connected to all input neurons indicating electrode forces by weight vectors \( W_j \). Then, only one neuron with the maximum output value converges to a high positive value for a standard pattern, and the others converge to zero. This means that only one output neuron with the nearest weights to the current input neurons is selected as ‘winner’. The winner output is represented as

\[
O_i = \begin{cases} 
1, & \text{if } i = c \text{ such that } ||X - W_c||^2 < \min_{i} ||X - W_i||^2, \quad i = 1, 2, \ldots, N_c \\
0, & \text{otherwise}
\end{cases}
\]

where \( O_i \) is the \( i \)th output value of output neurons, \( X \) is the input vector, \( W_j \) is the weight vector connected to \( i \)th output neuron, \( c \) is the winner output neuron and \( N_c \) is the number of winner output neurons.

<table>
<thead>
<tr>
<th>Class of quality*</th>
<th>Number of samples</th>
<th>Indentation (mm)</th>
<th>Shear strength (N)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Average</td>
<td>Standard deviation</td>
</tr>
<tr>
<td>I (I)</td>
<td>16</td>
<td>0.063</td>
<td>0.0076</td>
</tr>
<tr>
<td>P (P)</td>
<td>14</td>
<td>0.094</td>
<td>0.0067</td>
</tr>
<tr>
<td>G (G)</td>
<td>16</td>
<td>0.124</td>
<td>0.0046</td>
</tr>
<tr>
<td>R (R)</td>
<td>14</td>
<td>0.138</td>
<td>0.0065</td>
</tr>
<tr>
<td>E (E)</td>
<td>16</td>
<td>0.140</td>
<td>0.0041</td>
</tr>
</tbody>
</table>

*1 is the insufficient welding state, P is the poor welding state, G is the good welding state, R is the rich welding state and E is the excessive welding state.
Then, a set of weight vectors between the input and output neurons is defined and reproduced by iterations according to

\[
W_i(t + 1) = \begin{cases} 
W_i(t) + \alpha(t)[X(t) - W_i(t)], & \text{if } O_i = 1, \quad i = c \\
W_i(t), & \text{otherwise}
\end{cases}
\]

(3)

where \(\alpha(t)\) is the dynamic learning rate that decreases as \(t\) increases and normally is in the range \(0 \leq \alpha(t) < 1\). The weights of the winner are to be updated towards resembling the members in their own cluster. As the learning progresses, the electrode force patterns obtained by the experiment are classified into the standard electrode force patterns.

The same 78 sets of the electrode force patterns obtained before for the classification of welding quality classes are used to generate five sets of the standard patterns. Figure 5 illustrates the standard electrode force patterns generated by the proposed LVQ algorithm. The force profiles of the standard patterns indicate respectively the average value of their families. Their shapes are different mainly due to welding heat quantities according to the different welding currents for the given welding conditions. Some shapes of standard patterns shown in Fig. 5 are similar to those of electrode force profiles classified by the welding currents as shown in Fig. 3. In particular, the standard pattern 3 presents similar patterns to electrode force profiles in the case of 8kA welding current, showing good welding states with a proper amount of welding heat. Therefore, it is clear that the standard electrode force patterns can be used for the standard to classify the measured electrode force patterns for on-line monitoring and evaluation of their welding qualities, considering the characteristics of standard patterns.

### 3.2 Classification into the standard patterns

In this study, the Euclidean distance measurement method is used to match electrode force patterns to the standard patterns. The same 78 sets of the electrode force patterns as used for the classification of quality classes are also used to evaluate the performances of the proposed LVQ net. For the classified standard patterns, the shear forces and the indentations are shown in Fig. 6. The standard patterns 1 and 2 indicate poor welding qualities due to the weak shear strength below 4000N and small indentations below 0.1mm. On the other hand, the standard patterns 3, 4 and 5 indicate strong shear strength over 4000N except for some samples in the standard pattern 3, showing that the average values of shear strength are 4160, 4300 and 4500 N respectively. Also, the average values of indentation are 0.119, 0.133 and 0.141 mm respectively.
Therefore, the standard pattern 3 indicates good welding quality with the required strong shear strength and adequate small indentation. The standard pattern 4 indicates rich welding quality due to the large indentation, and the standard pattern 5 indicates excessive welding quality due to the very large indentation.

The welding states, quality evaluation and actions to improve the welding quality for the standard patterns are summarized in Table 2. Therefore, if the force patterns are changed to the standard pattern 3 by controlling the welding conditions with the welding parameters, a good welding quality can be obtained.

3.3 Evaluation of pattern classification

Evaluation results on the classification of the standard patterns by the standard welding quality classes are summarized in Table 3. The electrode force patterns in the welding quality classes 3 (G), 4 (R) and 5 (E) are exactly classified into the standard electrode force patterns 3, 4 and 5 respectively. On the other hand, six samples of 16 electrode force patterns in the welding quality class 1 (I) are classified into the standard electrode force pattern 2, and two samples of 14 electrode force patterns in the welding quality class 2 (P) are classified into the standard electrode force pattern 3. This is because the welding quality classes 4 and 5 are obviously distinctive, in comparison with the other classes, but some patterns of the welding quality classes 1, 2 and 3 are similar when classifying into the different standard patterns. When the difference in the Euclidean distance between the nearest standard pattern and the other standard pattern is small, the experimental force profiles may resemble two standard patterns.
Therefore, as shown in Fig. 6, it is clear that some samples with the relative higher strengths and indentations of class 1 are placed low in the standard pattern 2, and some samples with the relative higher strengths and indentations of class 2 are also placed low in the standard pattern 3. Thus, as shown in Table 3, the total success rate is 89.7 per cent, which is not high but is feasible for use in a real industrial application. If the samples are classified into three types of standard electrode force pattern, the total success rate can be 97.4 per cent, which is highly feasible for use.

### 4 CLASSIFICATION BY BP NEURAL NETWORK

#### 4.1 BP neural network structure

The BP neural network, which is a supervised neural network, with a multi-layer structure is proposed for precise classification. The first condition for applying the BP algorithm to the classification of electrode force patterns with 48 sampling points of forces in welding progress is to reduce the number of input data for fast and successful training and estimation. By careful investigation of the standard electrode force patterns shown in Fig. 5, it is clear that the measured electrode force patterns can be classified into slope patterns with five kinds of slope. Thus, as shown in Fig. 7, the slopes of the straight initial line and the smooth end line are very similar for all the patterns. Therefore, the measured electrode force patterns can be classified into slope patterns with three kinds of slope, which represent the welding characteristics of patterns. The initial slope and the middle slope represent the regions of force rise due to heat expansion, and the final slope represents the region of force drop due to shrinkage after the heat disappears. Then, three slope values of slope patterns can be used for the input data of the neural network estimator to be classified into the standard slope patterns.

Figure 8 shows the architecture of the proposed neural network, which consists of a preprocessing module and a trainable module. In the preprocessing module, the electrode force profiles are transformed to the simple tangent values of three slope angles through sampling for slope patterns. Then, the tangent values are used as input data for estimation by the trainable module. The tangent values of the three slope angles shown in Fig. 8 are calculated as

\[
S_1 = \frac{x_{16} - x_{10}}{0.16 - 0.10}, \quad S_2 = \frac{x_{27} - x_{16}}{0.27 - 0.16} \\
S_3 = \frac{x_{36} - x_{27}}{0.36 - 0.27}
\]

(4)

where \(x_i\) is the electrode force at the point \(i\) of 48 sampling points of force pattern during the welding.

| Quality evaluation and actions for the standard force patterns | | |
|---|---|---|---|
| Standard pattern | Weld state | Quality evaluation | Actions |
| 1 | Insufficient welding | Smaller indentation | Increase welding current more |
| 2 | Poor welding | Small indentation | Decrease electrode force more |
| 3 | Good welding | Proper indentation | Change the tip of electrode in the case of severe wear |
| 4 | Rich welding | Strong indentation | Increase welding current |
| 5 | Excessive welding | Larger indentation | Decrease electrode force |

<table>
<thead>
<tr>
<th>Quality classification</th>
<th>Number of samples</th>
<th>Number of samples in the following standard force patterns</th>
<th>Number that are subject to confusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (I)</td>
<td>16</td>
<td>10</td>
<td>6</td>
</tr>
<tr>
<td>2 (P)</td>
<td>14</td>
<td>12</td>
<td>2</td>
</tr>
<tr>
<td>3 (G)</td>
<td>16</td>
<td>16</td>
<td>0</td>
</tr>
<tr>
<td>4 (R)</td>
<td>16</td>
<td>16</td>
<td>0</td>
</tr>
<tr>
<td>5 (E)</td>
<td>16</td>
<td>16</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td>78</td>
<td>18</td>
<td>18</td>
</tr>
</tbody>
</table>

*1 is the insufficient welding state, P is the poor welding state, G is the good welding state, R is the rich welding state and E is the excess welding state.
Fig. 7 The standard force slope patterns

Fig. 8 Block diagram of the training and estimation procedures for electrode force slope patterns using the proposed BP neural network.
time of 0.48 s. $S_1$, $S_2$ and $S_3$ represent the tangent values of the initial slope, middle slope and final slope respectively.

The trainable module has the structure of a BP multi-layered neural network, which captures the output values of the preprocessing module as input data for classification. The multi-layered neural network is fully connected and consists of two hidden layers with nodes. The generalized delta rule, which was formulated by Rumelhart et al. [21] for learning the weights and the thresholds for multi-layered neural net, with BP of error is used for training the neural network. Now, the net input to a node in layer $j$ is defined as

$$\text{net}_j = \sum_i w_{ji} o_i(S_1, S_2, S_3)$$

where $w_{ji}$ is the weight connecting the hidden layers $i$ and $j$, and $o_i$ is the output of node $i$ entering node $j$. Then, the output of the node $j$ is represented by a sigmoid function as

$$o_j(S_1, S_2, S_3) = f(\text{net}_j) = \frac{1}{1 + \exp[-(\text{net}_j + \theta_j)]}$$

where $f$ is the activation function and $\theta_j$ represents the threshold altering the function shape. The neural network can estimate a wide variety of functional shapes with weights and thresholds. For the classification of slope patterns, the average system output error is defined as

$$E = \frac{1}{2P} \sum_p (t_{pl} - o_{pl})^2$$

where $P$ is the number of input samples, $p$ denotes each sample, $t_{pl}$ denotes the target value of the output layer $l$ for each sample $p$, and $o_{pl}$ denotes the output value of the output layer $l$ for each sample $p$.

In the generalized delta rule, the procedure for learning the correct set of weights is to vary the weights in a manner calculated to reduce the error as rapidly as possible. Then, the weight $w_{ji}$ might be modified to include a momentum term as follows:

$$\Delta w_{ji}(n + 1) = \eta \delta_j o_i + \alpha \Delta w_{ji}(n)$$

where the quantity $n + 1$ is used to include the $(n + 1)$th step, $n$ is the number of the current iteration, $\eta$ is the learning rate (normally $0 \leq \eta < 1$) and $\alpha$ is the momentum rate (normally $0 \leq \alpha < 1$). A large $\eta$ corresponds to rapid learning but might also result in oscillations of the average error. Generally, the learning rate $\eta$ and the momentum rate $\alpha$ are chosen by trial and error [22].

After the training procedure, the trained weights connected to each layer of neurons are generated and assigned to the three standard electrode force slope patterns, for the next estimation procedure. In the estimation procedure, the neural network estimator assigns the input of samples into a new output related to the standard slope patterns with trained weights, by comparing the similarities between the input neurons of samples and the trained weights of all the output neurons.

### 4.2 Training, estimation and evaluation

For the training, 25 representative samples of the electrode force patterns for quality classes are used to generate five sets of the standard patterns with five samples each. The learning rate $\eta = 0.7$, the momentum rate $\alpha = 0.5$, and the nodes in each hidden layer (ten in hidden layer 1; ten in hidden layer 2) are obtained with the best training convergence of average system errors, as shown in Fig. 9. Now, the proposed neural network estimator is trained with the experimental data to obtain the weights connected to the other layers. As the test patterns for the estimation, the same 78 profile data of the electrode forces as used for the LVQ net are also used to compare the performance of the BP net with the LVQ net mentioned in section 3.

Evaluation results on the classification of the standard slope patterns by the standard welding quality classes are summarized in Table 4. The samples in the welding quality classes 3 (G), 4 (R) and 5 (E) are classified into the standard electrode force patterns 3, 4 and 5 respectively, as in the LVQ neural network. On the other hand, two samples of 16 electrode force patterns in the welding quality class 1 (I) are classified into the standard electrode force slope pattern 2, and two samples of 14 electrode force patterns in the welding quality class 2 (P) are classified into the standard slope pattern 1. This is because the slope patterns of welding quality classes 3, 4 and 5 are obviously distinctive, in comparison with the other classes, but some slope patterns of the welding quality classes 1 and 2 are similar to each other, as shown in Fig. 7.

Therefore, as shown in Table 4, the total success rate becomes 95 per cent, which is feasible for use in a real industrial application. If the samples are classified into three types of standard electrode force pattern, the total success rate can be 100 per cent, which is successful for use. The evaluation results show that the proposed neural network is highly feasible for classifying various shapes of electrode force patterns with the standard slope patterns in real situations.

### 5 CONCLUSIONS

The pattern classification methods using algorithms based on LVQ and BP neural networks are proposed for the RSW process using a servo-controlled gun system. A series of experiments has been performed to
obtain electrode force patterns. The results evaluated with the standard welding quality classes prove the practical feasibility of the proposed classification methods. The main results can be summarized as follows:

1. The electrode force patterns can be classified into standard patterns by the proposed LVQ neural network for welding quality evaluation. The proposed LVQ method is quite feasible for classifying various

![Graph](attachment:image1.png)

(a) System errors according to the variations of learning rate (L.R.) and momentum rate (M.R.): H.L.1 = 10, H.L.2 = 10

![Graph](attachment:image2.png)

(b) System errors according to the variations of hidden layer 1 (H.L.1) and hidden layer 2 (H.L.2): L.R = 0.7, M.R. = 0.5

**Fig. 9** System errors for various training parameters

<table>
<thead>
<tr>
<th>Quality class*</th>
<th>Number of samples</th>
<th>Number of samples in the following standard force patterns</th>
<th>Number that are subject to confusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (I)</td>
<td>16</td>
<td>14 14 2 2 2 2 2 2</td>
<td>2</td>
</tr>
<tr>
<td>2 (P)</td>
<td>14</td>
<td>14 2 12 12 12 12 12 12</td>
<td>2</td>
</tr>
<tr>
<td>3 (G)</td>
<td>16</td>
<td>16 16 16 16 16 16 16 16</td>
<td>2</td>
</tr>
<tr>
<td>4 (R)</td>
<td>16</td>
<td>16 16 16 16 16 16 16 16</td>
<td>4</td>
</tr>
<tr>
<td>5 (E)</td>
<td>16</td>
<td>16 16 16 16 16 16 16 16</td>
<td>4</td>
</tr>
<tr>
<td>Total</td>
<td>78</td>
<td>14 16 14 16 16 16 16 16</td>
<td>4</td>
</tr>
</tbody>
</table>

*1 is the insufficient welding state, P is the poor welding state, G is the good welding state, R is the rich welding state and E is the excess welding state.
shapes of electrode force patterns with the fast classification speed in real situations, demonstrating a total success rate of 89.7 per cent for five standard patterns, and 97.4 per cent for three standard patterns.

2. The electrode force patterns can also be classified into standard slope patterns by the proposed BP neural network for the welding quality evaluation. The proposed BP method shows the precise classification into the required weld qualities, giving a total success rate of 95 per cent for five standard patterns, and 100 per cent for three standard patterns, but it takes a longer time for classification than the LVQ method.

3. In the practical use of the servo-controlled welding system for automatic RSW processes, the proposed approach will provide efficient and reliable classification results. Therefore, the welding quality evaluation by classification methods of electrode force patterns using the proposed neural networks can be used with satisfactory accuracy for on-line quality monitoring and quality enhancement.

REFERENCES


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