Time frequency feature extraction of the arc energy for quality detection of the aluminum alloy double pulse MIG welding

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Abstract
In aluminum alloy double pulse metal inert-gas (DPMIG) welding, the outputting arc current waveform is distorted under the influence of various factors such as harmonics and impact loads. The arc distortion of aluminum alloy DPMIG welding affects the arc stability and welding quality. Based on the collected welding current signal, a feature extraction method is proposed for quality detection of the aluminum alloy DPMIG welding. The wavelet method is adopted to eliminate the noise of the welding current signal. The local mean decomposition (LMD) is performed to the welding current signal to obtain a series of Product Function (PF) components with real physical meaning. The Hilbert transformation is subsequently performed to the PF components to obtain the time frequency distribution of welding arc signal energy. The approximate entropy (ApEn) of the time frequency distribution of the welding current signal is calculated to evaluate the arc stability and the welding formation quality. Application of the proposed feature extraction method indicates that the combination of the wavelet and LMD can effectively extract the distortion components of the welding current signal. The time frequency distribution of the PF components of the welding current can clearly reflect the concentration and dispersion of the arc energy. The approximate entropy of the time frequency distribution of the welding current can be quantitively reflect the arc stability and the welding formation quality in the aluminum alloy double pulse MIG welding.

Keywords: Aluminum alloy metal inert-gas welding, Wavelet, Local mean decomposition, Hilbert transform, Time-frequency distribution, Approximate entropy

1. Introduction

Aluminum alloy owns the advantages of the small density, high specific strength, good corrosion resistance, good formability and low cost, which has been widely used in automobiles, high-speed trains, aerospace, shipbuilding, nuclear industry and ordnance industry (Kaufman, et al., 2007; Merklein, et al., 2002). The DPMIG welding is a main effective manufacturing process to the aluminum alloy with the high mechanical performance according to the appropriate process of the welding speed and frequency. In the appropriate frequency range, the low frequency modulation easily excites the resonance of welding molten pool, which inhibits the generation of pores. The stirring affected on molten pool during welding is helpful to refine grain. The grain refinement can improve mechanical properties and reduce crack sensitivity.

The alternating change of the arc in aluminum alloy DPMIG welding process causes the variation of the temperature among the electrode surface. The arc resistance is not constant as a changing of the current. The arc current and voltage waveform are irregular due to the influence of the electrical characteristics of the welding power and external interference. The distortion of the current and voltage waveform makes the arc energy distribution uneven, which directly affects the arc stability and the welding formation quality. The time and frequency domain characteristic information related to the arc stability and the welding formation quality is contained in the arc current distortion. The factors that affect the welding arc stability mainly come from the common welding parameters such as arc voltage, current, welding speed and welding wire diameter (Sevim, et al., 2013). Xu adjusted the arc length to ensure the arc stability by increasing or reducing the fundamental time of the average current according to the pulse frequency modulation (Xu, et al., 2018). Yao discussed the relationship among the width of welding seam, frequency and welding speed according to changing of the current, frequency and welding speed respectively during aluminum alloy double pulse
welding experiment (Yao, et al., 2009).

Welding process monitoring and evaluation based on electrical parameters are important to ensure the welding quality and increase production efficiency. As early as in 1980, characterization of spot welding behavior by dynamic electrical parameter monitoring was researched by Dickinson et al (Dickinson, et al., 1980). Automatic image processing was introduced to monitor the welding processes successively (Eckelt, et al., 1989). In recent years, the introduction of advanced technology to monitoring and evaluation of welding process has become research focus. Wu used a fuzzy logic system to achieve process monitoring and quality evaluation in GMAW based on electrical parameters (Wu, et al., 2001). The theory of stochastic processes was applied to the analysis of gas metal arc welding data (Alfaro, et al., 2006). Welding joint strength prediction was implemented by wavelet packet analysis based on arc current (Pal, et al., 2008). In order to obtain more welding information, the multi-parameter testing system was also appeared in welding monitoring and evaluation (Cullen, et al., 2008; Ru-Xiong, et al., 2012). At the same time, nonlinear time series processing methods have also become an important mean for analysis of arc stability in welding process monitoring and evaluation. This effect was also well studied and a lot of practical applications could be found (He, et al., 2013; Li, et al., 2013). Based on the experimental non-linear time series of welding current at different frequency and duty cycle, He numerically evaluated the arc stability of Square Wave Alternating Current Submerged Arc Welding (SW AC SAW) by the largest Lyapunov exponents (He, et al., 2013). Li accurately calculated the maximum Lyapunov exponent of the welding processes for different parameters to evaluate stability of the welding process in gas metal arc welding (GMAW) (Li, et al., 2013).

Due to the uncertainty and nonlinear coupled factors influencing on the welding quality, the collected data is the non-stationary signal. In addition, the high frequency noise is inevitably superimposed to the welding arc signal due to the arrangement of cable line and external electromagnetic interference. The time-frequency analysis method is most powerful tool for non-stationary signals presently. There are some time-frequency analysis methods such as window flourier transformation, continuous wavelet transformation, Wigner-Ville distribution, Hilbert-Huang transformation (HHT) and LMD (Flandrin, et al., 2013; Hsu, et al., 2013; He, et al., 2013; Smith, 2005). LMD is a new self-adapting time-frequency analysis method, and first proposed by Jonathan S. Smith, which get better results by applying to the EEG signal processing. Liu (Flandrin, et al., 2013) proposed a fault feature extraction method to evaluate the non-stationary characteristics of the fault rolling bearings based on LMD and multi-scale entropy. Liu (Hsu, et al., 2013) proposed a modulation information extraction method for gear fault diagnosis based on LMD. He (He, et al., 2013) proposed a method based on LMD and support vector machine to quantitatively estimate the rationality of welding parameters and the quality of welding. LMD method can adaptively decompose a complex multi-component signal into a number of instantaneous frequency and physical meaning PF components. Each of the PF components is multiplied by an envelope signal and a pure frequency modulation signal. It has higher time-frequency resolution and concentration, which is especially suitable for the analysis of the non-stationary signals. The LMD method has been widely applied in the field of manufacturing quality detection and fault diagnosis. The HHT is also an effective signal processing method developed by Huang (Smith, 2005), which has been applied in the ocean surface waves, wind waves and fluids. The HHT consists of two parts. The first part is empirical mode decomposition (EMD) (Du, et al., 2018), which is used to decompose the signal into a series of IMF components. The second part is a Hilbert transformation, which transform each IMF component to obtain the energy Hilbert spectrum on the time frequency plane. HHT has been successfully applied to the manufacturing and fault diagnosis field (Rai, et al., 2007; Peng, et al., 2005; He, et al., 2013).

Welding current is the main energy parameter of the aluminum alloy DPMIG welding. The wavelet and LMD are performed to the welding current signal for purpose of de-noising and extracting the distortion components. The Hilbert transformation and approximate entropy are presented to describe quantitatively the time frequency distributions of the welding arc energy related to the arc stability and welding formation quality. It is helpful to obtain the new knowledge of arc characteristic of the aluminum alloy double pulse MIG welding, and get accurate numerical evaluation of arc stability and welding quality. The paper is organized as follows. In Section 2, the collected arc electrical signal model is qualitatively established to analyze the compositions related to the arc stability and the welding seam formation. In Section 3, we discuss the theory and algorithm of the wavelet and LMD, Hilbert transformation and the calculation of the approximate entropy, and how the above methods applied to the collected welding current signal. In Section 4, the experimental condition is described, the welding current signal is calculated and analyzed, and the calculated results are discussed. The conclusions are summarized in Section 5.

2. Arc signal model

In the process of aluminum alloy DPMIG welding, the outputting arc current and voltage waveform of the welding power
source are affected by various factors such as harmonics, impact load and so on. The collected arc signal basically contains the regular outputting electrical waveform of the power supply, the distortion part caused by electric transformation process and arc load and the noise of the electromagnetic and environment. In order to analyze effectively the compositions of the collected arc electrical signal related to the arc stability and the welding seam formation. The arc signal model is established considering the three components of the collected arc electrical signals during welding. The arc model of the collected welding electrical signal can be qualitatively described by the following expression.

\[ u(t) = u_0(t) + \sum_k u_k(t) + \sum_n u_n(t) \]  

(1)

Among them, \( u_0(t) \) is the ideal output waveform signal by the welding power supply, which determines the stability of the arc energy and the welding seam formation. \( u_0(t) \) is the regular pulse current and voltage waveform, which is determined by the characteristics of the power supply and the setting of the process. \( \sum_k u_k(t) \) is the distortion part of the current and voltage waveform caused by harmonic and impact and random load, which affects the arc stability and welding seam formation. \( \sum_n u_n(t) \) is the noises of the switching, electromagnetic and environment in the welding power supply, which affects the results of the detection and analysis. The feature extraction of the welding arc signal is used to detect the arc stability and the welding seam formation quality, of which the key is to separate the distortion part \( \sum_k u_k(t) \) from the arc signal containing noise.

3. Method of signal processing and feature extraction

3.1 Wavelet de-noising

The purpose of the de-noising is to eliminate the noise part \( \sum_n u_n(t) \) from the signal \( u(t) \), which retains the welding arc signal part \( u_0(t) + \sum_k u_k(t) \). During the wavelet is performing to the collected welding arc signal for de-noising, the high frequency wavelet coefficients that mainly contains noise are processed using the threshold method. The wavelet de-noising process is as follows (Su, et al., 2018).

(1) The wavelet function is selected and the layer of decomposition \( N \) is determined, which decompose the welding arc signal \( u(t) \) into the \( N \) layer components by the following formula.

\[ c^j = H c^{j-1} \]
\[ d^j = G d^{j-1} \]  

(2)

Where \( x(t) = c^0, j=0\sim J \), and \( J \) are the largest decomposition layers. \( H \) is the low pass filter. \( G \) is a high pass filter. \( c^j \) and \( d^j \) are the low and high frequency components of the original signal at the \( 2^{-j} \) resolution respectively.

(2) The threshold values are selected to quantize the each layer’s high frequency wavelet coefficient. The soft threshold is defined as following:

\[ W(d^j, T) = \begin{cases} \text{sgn}(d^j)|d^j|, & |d^j| \geq T \\ 0, & |d^j| < T \end{cases} \]  

(3)

Where, \( T \) is a threshold value, and \( W(d^j, T) \) is a threshold quantized signal.

(3) The destination signal is reconstructed according to the high frequency wavelet coefficients after performing quantization process.

\[ C_j = H^* c^{j-1} + G^* W(d^{j-1}, T) \]  

(4)
Where, $H^*$ is the dual operator of $H$, and the $G^*$ is the dual operator of $G$.

Figure 1 is a set of pulse waveform of the welding current signal of DPMIG and the wavelet de-noising result.

![Image](image_url)

(a) The collected original welding current signal  
(b) The wavelet de-noising current signal

Fig. 1 The welding current signal of DPMIG and the wavelet de-noising result

It can be seen from Fig.1 that the noise superimposed on the welding arc signal has been eliminated effectively by wavelet de-noising method. The waveform of welding arc signal becomes clearer, of which the singular points and the transient distortion are highlighted. The wavelet de-noising is performed to the welding arc signal, which can contribute to the succeeding investigation of the arc stability and the welding seam formation.

### 3.2 LMD

The LMD is a demodulation process for a multi-component signal. LMD adaptively decomposes a complex multi-component signal into a series of $PF$ components with a physical meaning of instantaneous frequency. Each $PF$ component consists of an envelope signal multiplied a pure frequency modulation signal. The instantaneous envelope is representation of the amplitude modulation information of the $PF$ component. The instantaneous frequency is representation of the frequency modulation of the $PF$ component. According to demodulation process for a multi-component signal by LMD, an arbitrary time series signal $x(t)$ can be represented by the sum of $PF_p$ component and a monotonic function $u_j$ as following.

$$
x(t) = \sum_{p=1}^{k} PF_p(t) + u_j(t)
$$

The LMD is performed to the de-noising welding current signal $x(t)$ of the Fig.1. The Fig.2 is the decomposition results.

![Image](image_url)

Fig. 2 LMD decomposition results

As can be seen from Fig.2, the decomposed components of $PF1$ and $PF2$ correspond to the different frequency signal, which represents the real physical information within the welding current signal. The monotonic function $u_j$ is the rule pulse waveform. Each $PF$ represents the distortion components of double pulse current waveform with different frequencies and amplitude diversification in the time scale. The characteristics of original signal become visible in different resolutions. The amplitudes of the $PF$ components vary greatly. The energy distribution of $PF$ component of the arc signal varies when the welding
process parameters changes accordingly, which directly affects the arc stability and welding seam formation. In order to extract the arc energy feature, the time frequency distribution of the decomposed PF components are calculated by the Hilbert transformation, which is used to characterize the differences for evaluating the arc stability and welding seam formation.

3.3 Hilbert transform for PFs

According to Eq. (5), Hilbert transform is performed to each PF as following.

\[
\widehat{PF_p}(t) = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{PF_p(\tau)}{t-\tau} d\tau
\]

(6)

The analytic signal \( z_i(t) \) is constructed by Eq. (7).

\[
z_i(t) = PF_p(t) + j \widehat{PF_p}(t) = a_i(t)e^{j\Phi(t)}
\]

(7)

The amplitude function \( a_i(t) \) and phase function \( \Phi_i(t) \) are represented by Eq. (8) and Eq. (9).

\[
a_i(t) = \sqrt{PF_p^2(t) + \widehat{PF_p}^2(t)}
\]

(8)

\[
\Phi_i(t) = \arctan \frac{\widehat{PF_p}(t)}{PF_p(t)}
\]

(9)

The instantaneous frequency \( f_i(t) \) can be further represented as following.

\[
f_i(t) = \frac{1}{2\pi} \omega_i(t) = \frac{1}{2\pi} \frac{d\Phi_i(t)}{dt}
\]

(10)

In this way, the \( x(t) \) can be represented as following.

\[
x(t) = RP \sum_{i=1}^{N} a_i(t)e^{j\Phi_i(t)} = RP \sum_{i=1}^{N} a_i(t)e^{j\int_{t_0}^{t} \Phi_i(\tau) d\tau}
\]

(11)

Where \( RP \) is real part, Eq. (11) is defined as Hilbert spectrum and can be represented as following.

\[
H(\omega_i,t) = RP \sum_{i=1}^{N} a_i(t)e^{j\int_{t_0}^{t} \Phi_i(\tau) d\tau}
\]

(12)

In the Eq. (12), it is described accurately that the amplitude of the signal varies as the time and frequency. The signal amplitude can be depicted by the contour lines of time frequency plane, and it can also be expressed as a function of time and instantaneous frequency in three dimensional space.

3.4 Approximate entropy for Hilbert spectrum

In order to quantify the energy characteristics at different welding parameters, the approximate entropy is introduced to the Hilbert spectrum of the welding current signal. The specific method divides the time frequency plane into \( M \) parts, each of which is represented by \( \{u(i), i=0,1, \cdots, M\} \). The time frequency energy of the welding current signal is composed by a time series of \( \{u(i), i=0,1, \cdots, M\} \). According to the definition of approximate entropy (Wang, et al., 2010), the calculation method is arranged for describing the time frequency distribution of the arc energy in aluminum alloy DPMIG welding as following.

(1) The values of the mode dimension \( m \) and the similar tolerance \( r \) are given in advance. According to the time serial numbers of the \( \{u(i), i=0,1, \cdots, M\} \), a group of \( m \) dimensional vectors are constructed.
\[ X(i) = [u(i), u(i+1) \ldots u(i+m-1)] \]

Where \( i = 1 \sim M - m + 1 \)

(2) The distance between the vector \( X(i) \) and \( X(j) \) is calculated. The distance is the maximum one in the absolute value of the difference between the vector \( X(i) \) and \( X(j) \).

\[
d[X(i), X(j)] = \max_{k=0 \sim m-1} |u(i+k) - u(j+k)|
\]

(3) According to the given threshold \( r \) (\( r > 0 \)), the number satisfied the condition of \( d[X(i), X(j)] < r \) and ratio to the total vector number \( M - m + 1 \) are counted, which is remarked by \( c^+_{m} (r) \).

\[
c^+_{m}(r) = \frac{\text{the number of } r}{(M - m + 1)}
\]

(4) The logarithm of \( c^+_{m} (r) \) is removed firstly, and the average value of all \( i \) is calculated, which is remarked by \( \Phi^+_{m} (r) \).

\[
\Phi^+_{m} (r) = \frac{1}{N - m + 1} \sum_{i=1}^{N-m+1} \ln c^+_{m}(r)
\]

(5) For the number of \( m+1 \), the steps from one to four are repeated to obtain \( \Phi^+_{m+1} (r) \).

The approximate entropy is defined as following.

\[
\text{ApEn}(m,r) = \lim_{N \to \infty} \left[ \Phi^+_{m} (r) - \Phi^+_{m+1} (r) \right]
\]

The value of ApEn is obviously related to the values of \( N, m \) and \( r \). According to the experiment, Pincus proposed the approximate entropy has more reasonable statistical property when \( N=75 \sim 5000 \), \( m=2 \) and \( r = 0.1 \sim 0.25\text{SD}(u) \), the SD is the standard deviation of the time series (Fjordholm, et al., 2017). The approximate entropy of the AE signal is calculated under \( m=2 \) and \( r = 0.15\text{SD}(u) \).

4. Experiment and results

With objects of experiments and analysis to the aluminum alloy double pulse MIG welding, welding arc current signal is collected by the current sensor, Ethernet data acquisition and industrial control computer. The experimental platform is shown in Fig. 3. The collected welding current signal is transported to industrial control computer by cable transmission. The collected
signal are analyzed and processed by MATLAB. Experiments are done by the double pulse MIG welding machine and robot. The material of work piece is 6061 aluminum alloy with slab thickness of 5mm. The argon flow rate is 10 L/min. The welding wire is important in aluminum alloy double pulse metal inert-gas (DPMIG) welding. Brand of welding wire is ER5356. The main fused metal mechanical properties of ER5356 are yielding value of 120 Mpa, tensile strength of 265 Mpa and percentage elongation 26. The melting metal chemical composition of ER5356 are Si(<0.25), Fe(<0.40), Cu(<0.10), Mn(0.05~0.20), Mg(4.50~5.50), Zn(<0.10), Ti(0.06~0.20) and Cr(0.05~0.20%). The elongation of the welding wire is 15 mm, and the diameter of the welding wire is 1.2mm. During the welding experimental process, different welding process parameters are set up. The welding arc current signals are collected during the welding process. The sampling frequency is 4kHz. 8000 points data of the collected arc current signal of each welding experimental process are selected for succeeding analyzing and processing.

In aluminum alloy DPMIG welding, the welding speed and current waveform frequency are the main process parameters that affect the arc stability and welding quality. During the welding process testing and verification, the welding effects under condition of the different welding speed and current waveform frequency are investigated. In order to reflect the welding effects of the different welding speed and current waveform frequency, the front three group experiment mainly investigate the comparison of welding effects of the different welding speeds with the same other parameters. The fourth group parameter is set to be the same welding speed and different current waveform frequencies that is compared to the third ones. Therefore, four groups of welding process parameters are selected for the experiment, which is shown in Table 1, and the welding current signals are collected simultaneously for analysis and processing. The welding parameters and molding situation are shown in Table 1.

| Experiment number | Welding speed (mm/s) | Peak value current (A) | Base value current (A) | Peak voltage (V) | Base value voltage (V) | Duty cycle (%) | Frequency (Hz) | Welding molding situation |
|------------------|---------------------|-----------------------|-----------------------|----------------|-----------------------|---------------|----------------|-------------------------|
| 1                | 1                   | 90                    | 40                    | 21             | 17.5                  | 50            | 2              | Normal, undercut        |
| 2                | 1.5                 | 90                    | 40                    | 21             | 17.5                  | 50            | 2              | Normal                 |
| 3                | 5                   | 90                    | 40                    | 21             | 17.5                  | 50            | 2              | Hump                   |
| 4                | 5                   | 100                   | 40                    | 21             | 17.5                  | 50            | 5              | Normal                 |

Figure 4 is the appearance of the welding seam formation and cross section of each group experiments. The welding molding situation of the experiments are normal (welding seam surface is neat and smooth), undercut (welding seam surface is corner, irregular and depression) and hump (welding seam surface is obvious rugged, uncontinuous and depression).

Figure 5 is the process of the feature extraction by wavelet de-noising and LMD.

(1) Welding experiments are done by the given welding process parameters, and conduct welding arc current signal data acquisition, the welding current is sampled real time for 25s at a sample rate of 4 kHz. From the total samples, 8000 data points are extracted for succeeding analyzing and processing.

(2) Wavelet de-noising is performed to the selected signal to eliminate the noise. The high frequency wavelet coefficients that mainly contain noise are processed using the threshold method.

(3) The LMD is performed to the de-noising welding current signal. The welding arc current signal is decomposed into $N_{PF}$ components.

(4) Hilbert transform is performed to the $PF$ components to get the time frequency distribution. The time frequency plane is divided into $M$ parts, each of which is represented by $\{u(i), i = 0, 1, \cdots, M\}$.

(5) The approximate entropy of $\{u(i), i = 0, 1, \cdots, M\}$ is calculated, which is used to evaluate the rationality of welding process, arc stability and welding molding quality.

Figures 6(a)-9(a) is the waveform of the welding current signal by the wavelet de-noising, which corresponds to each welding parameter in table 1. Fig.6 (b) - 9(b) shows the joint distribution of the time and frequency after Hilbert transform for the welding current signal demodulated by LMD. It can be seen from Fig.6 (b) - 9(b), that the joint distribution of the time and frequency accurately reflects the variation rule of signal’s frequency, amplitude with high time-frequency resolution and concentration.
(a) The welding seam appearance and cross section of the sequence number one

(b) The welding seam appearance and cross section of the sequence number two

(c) The welding seam appearance and cross section of the sequence number three

(d) The welding seam appearance and cross section of the sequence number four

Fig. 4 The welding seam appearance and cross section

The collected welding current signal \[\rightarrow\] Wavelet de-noising \[\rightarrow\] LMD decomposition

Evaluation of the arc stability and welding formation quality \[\rightarrow\] ApEn calculation \[\rightarrow\] Hilbert transformation

Fig. 5 The flow chart of feature extraction for the welding arc signal
In Fig. 4 and Figs. 6-9, the time frequency distribution of the welding current signals collected in each experiment and welding seam formation are observed. The welding seam surface of the experiment number three are obvious rugged.
uncontinuous and depression. The corresponding current waveform of the experiment number three is an obvious interrupting phenomenon. The time frequency distributions of the experiment number three contains more sideband frequency components compared to the others. The other welding seam surface is relative regular, the corresponding welding current waveform is also a regular periodic pulse alternant waveform, the time frequency distribution of the arc energy fluctuates around the main frequency components of 2Hz and 5Hz with a small amount of other sideband. Thus it can be seen that the degree of the welding current waveform distortion and the frequency components directly affect the arc energy distribution and the welding seam formation.

Figure 6, 7 and 8 are the time frequency distribution in the same frequency and duty cycles with different welding speed. The time frequency distribution of the welding current signal is relatively clear in frequency and time. The main components of the time frequency spectrum fluctuate around the frequency of 2Hz. The three group time frequency distributions of the welding current signals show that the arc energy is different over time and frequency. The arc energy distribution varies as the welding speed. The other frequency components are obviously increased as the welding speed under the same condition.

Figure 8 and 9 are the time frequency distribution in the same duty cycles and speed with different frequency. The main frequency components of each group signal are basically around 2 Hz and 5Hz, and there are other distortion components. The different time frequency distributions of the two group signals mainly exist in the amplitude diversification as frequency. The other components are relatively less as a increasing of the frequency under the same condition, and the arc energy is more concentrated.

In order to quantify the arc energy stability in the time and frequency domain under the different specifications of the double pulse MIG welding. The approximate entropies of the welding current signals are calculated to quantitatively characterize the arc stability and welding formation. The calculation results are shown in Fig.10. The average of the approximation entropy of each group is shown in Table 2.

![Fig.10 The approximate entropy of the experimental current signal corresponding to each group](image)

**Table 2 Approximate entropy of the current signal corresponding to each experiment**

| Experiment number | 1     | 2     | 3     | 4     |
|-------------------|-------|-------|-------|-------|
| Approximate entropy | 0.262 | 0.338 | 0.469 | 0.393 |

Comparing to the calculated approximate entropy form the first to third row in Table2, the approximate entropy becomes larger as the welding speed increases. The welding speed changes form 1mm/s to 5mm/s at the same frequency and duty cycle, the welding seam formation becomes poor and appears hump, the calculated approximate entropy is larger. When the frequency of pulse is changed from 2Hz to 5Hz, the welding seam formation becomes good and restores to be normal, the calculated approximate entropy becomes smaller relatively. As an increasing of the frequency matched the high welding speed, the welding arc energy is relatively concentrated, the welding process becomes more stable, and the calculated approximate entropy of the corresponding welding current signal energy becomes smaller. The stability of welding process becomes better as the current frequency increases in welding process. Therefore, the approximate entropy can be used as the stability judgment criteria for the
double pulse MIG welding in condition of the same duty cycle and different frequency of current waveform. It indicates that it can keep the arc stability and welding quality at high welding speed by heightening the frequency of current waveform appropriately in the welding process.

The changing of welding speed and frequency will lead to different distribution of arc energy at time and frequency domain in aluminum alloy double pulse MIG welding, which influences the welding arc stability and the welding seam formation. Therefore, the uniform distribution of the arc energy in the time and frequency domain can be effectively obtained by the reasonable collocation of the welding current waveform parameters, which ensure the welding arc stability and welding seam formation.

5. Conclusions

Based on the wavelet, LMD and Hilbert transform, a time frequency feature extraction method for the welding arc current signal in aluminum alloy double pulse MIG welding is proposed. The approximate entropy of the time frequency feature of the welding arc current signal is used as a characteristic parameter to evaluate the arc stability and welding molding quality. The effectiveness of the method is verified by experimental analysis. The results are summarized as follows.

1) Wavelet transform has been performed to the welding arc current signal for de-noising in aluminum alloy double pulse MIG welding. The noise superposed on the welding current signal can be effectively eliminated. The valid components related to the arc stability and welding seam formation can be retained. Thus, the wavelet de-noising to the welding current signal can contribute to the succeeding investigation of the arc stability and the welding seam formation.

2) The LMD has been performed to the de-noising welding current signal to extract the distortion components. The welding arc current signal is decomposed into a series of PF components with the independent physical information of instantaneous frequency, which relates to the arc stability and the welding seam formation separately.

3) Hilbert transform is performed to the PF components to get the time frequency distribution of welding arc current signal, which can effectively describe and estimate arc energy characteristics related to the arc stability and the welding seam formation. The approximate entropy of the time frequency distribution of welding arc current signal has been also calculated to be a numerical index for evaluating the arc stability and the welding seam formation. It provides an effective method for the online evaluating of the aluminum alloy double pulse MIG welding.

The state in aluminum alloy DP-MIG welding process is complex. In order to improve the effectiveness and precision of the works and results, the further work will be considered as following:

1) The experimental method and conditions of the aluminum alloy MIG welding process is necessary to be further improved.

2) The reasonable experimental programs and quantities should be designed and implemented to quantitatively determine the relationship between the welding surface appearance and the characteristic parameters of welding current signal.

3) Metallographic studies and mechanical performance testing experiment of the welding seam of the inspected specimen should be considered to validate the use of the proposed methodology.

4) The construction or selection of wavelet base functions and parameter optimization should be considered for reaching the more de-noising effect. The appropriate interpolation function of LMD will be also deeply concerned for decomposition of the welding arc signal with higher precision.

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