TELKOMNIKA, Vol.14, No.3, September 2016, pp. 948~955
ISSN: 1693-6930, accredited A by DIKTI, Decree No: 58/DIKTI/Kep/2013
DOI: 10.12928/TELKOMNIKA.v14i3.3589

Application of Nonlinear Dynamical Methods for Arc Welding Quality Monitoring

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Abstract

Owing to its diverse, the stability of arc signals in high-powered submerged arc welding is not very salient, and weld defects are difficult to detect automatically. Aimed at this problem, this paper proposes a noise robustness algorithm for calibrating the singularity points and denoting the kinetics and stability of arc. Firstly, reconstruct a vector, which is the calculation of the approximate entropy in phase space, denotes the distortion of arc. Then, a algorithm for calculation is given based on reconstruction of chaotic time series in phase space. Finally, we apply the calculation of approximate entropy algorithm in phase space to flaw detection for arc signals, which is efficient proved by experimental results.

Keywords: *weld defects, singularity points, phase space, approximate entropy*

1. Introduction

With the development and application of automation technology and computer technology, the digitization and intelligent of welding has become a focus of the development of welding technology nowadays.Welding process is a complex physical and chemical process with various interference, and the stability of welding quality control is a more complex and difficult nonlinear problem [1-3]. Electrical signals,such as welding current and welding voltage,contains abundant information of welding process.If we can extract the feature information accurately,and then using the scientific method to undertake statistical analysis and calculation,will surely can be better sight into the characteristics of the mechanism of welding process [4, 5]. Many scholars have studied in this respect: to reduce the subjectivity of double wire pulsed welding welding process stability evaluation. Considering weld strength as the quality characteristic in the selection of process parameters, fume formation in a pulsed gas metal arc welding (GMAW) process is investigated by coupling a time-dependent axi-symmetric two-dimensional model, which takes into account both droplet detachment and production of metal vapour, with a model for fume formation and transport based on the method of moments for the solution of the aerosol general dynamic equation [6]. Three geometry changes to the inner bore of a welding nozzle and their effects on weld quality during gas metal arc welding (GMAW) were investigated through the use of computational fluid dynamic (CFD) models and experimental trials [7]. An adaptive technique based on estimation of signal parameters via rotational invariance technique (ESPRIT) is proposed that optimizes the accuracy and computation time for harmonic/interharmonic estimation of stationary as well as nonstationary power supply signals [8]. The use of fuzzy rule based systems to model the relationship between weld control parameters and the weld bead geometry features is explored in this paper. The system is tested on three datasets and the performance is found to be satisfactory compared to the multilayer perceptron (MLP) and radial basis function (RBF) neural networks based systems [9]. Simpson S W elucidates the signature image approach to welding fault detection, covering the calculation of signature image data objects from blocks of welding electrical data (voltage and current), the definition of appropriate vector operations, and the manipulation of the signatures to permit detection of welding faults [10].

The above analysis of the status of the system is not comprehensive, the extracted characteristic information is more rely on the experience of the people,and overemphasize on the independence of the state. Loss time-varying characteristics of the signal, and ignore the

Received May 2, 2016; Revised Jul 6, 2016; Accepted July 20, 2016

parameters in chronological associated factors, such as the thermal inertia of arc space. Therefore, in time series, data gather of every moment reflects as dependence relationship. In the early 1960, in order to overcome the difficulty to solve the entropy in the chaos phenomenon, Pincus proposed a concept of approximate entropy, which is a non-negative quantitative description of the complexity of the nonlinear time series. If the physical process of a nonlinear complex degree is higher, the approximate entropy will be bigger [11-13]. This method is of the advantages of short demanded data and the advantages of strong anti-interference capability. In practice, it often be used to a diagnostic criterion,and already have tried and is a huge success in the fields of atmospheric research [14], mechanical equipment fault diagnosis [15], telecommunications [16, 17], power transmission [18].

Although ApEn method can identify dynamic structure mutation of time series, it will not be able to give jump time and the detected mutation interval that heavily rely on the choice of the subsequence. Therefore,the author built calculation of approximate entropy algorithm to solve the dynamic arc time series of approximate entropy value. The present paper is mainly devoted to theproblem of exploring arc and process stability in high-powered submerged by virtue of the chaotic parameter, ApEn. In particular, the goal of the paper is to attempt to propose a new numerical standard to accurately quantify and evaluate the arc stability in high-powered submerged arc welding.

2. Research Method

2.1. The Definition of Burst Detection ApEn Algorithm

Step 1. Mirror the data $f(n)$ and expand to L, that build-up the new sequence $g(n)$;

$$g(n) = f(-n+2L) + f(n), n = 1, 2, ..., L \quad (1)$$

Step 2. Reconstruct $T(n)$ as a L -dimensional of phase space;

$$T(n) = \{g(i+1), g(i+2), ..., g(i+L)\}, i = 1, 2, ...L \quad (2)$$

Step 3. Calculate the ApEn value of $d\ T(n), n = 1, 2, ...L$ by fast approximate entropy calculation;

Step 4. Reconstruct $Y(n), n = 1, 2, ...L$ as a L -dimensional of phase space;

Step 5. Sequence the $Y(n)$, if the record breakdown threshold point, record the breakdown point coordinates x0, at (x0, x0 + L) within the scope of retrieving the maximum entropy point of singularity.

2.2. The Definition of Fast ApEn

In order to define ApEn(r,m,N) for an N-dimensional time series $\{\varepsilon_1, \varepsilon_2, ..., \varepsilon_N\}$, given the parameters m,r, the m-dimensional embedded vector $x(i) = \{\varepsilon_1, \varepsilon_2, ..., \varepsilon_{i+m-1}\}$, have been to be considered. Then, the ApEn is defined as [10]:

$$ApEn(m, r, N) = \lim_{N\to\infty} \left|\phi^m(r) - \phi^{m+1}(r)\right| \quad (3)$$

Where:

$$\phi^m(r) = \left(\frac{1}{N-m+1}\right) \sum_{j=1}^{N-m+1} \ln C_i^m(r) \quad (4)$$

$$C_i^m(r) = \left(\frac{1}{N-m+1}\right) \sum_{j=1}^{N-m+1} \theta\left(d\left(\varepsilon_i^m, \varepsilon_j^m\right) - r\right) \quad (5)$$

$$\theta(x)=\begin{cases}1 & if \quad x>0\\ 0 & otherwise\end{cases} \tag{6}$$

And,

$$d_{ij}=\max\left|\varepsilon(i+k)-\varepsilon(j+k)\right|, 0\le k\le m-1 \tag{7}$$

$$C_i^2(r)=\sum d_{ij}\cap d_{(i-1)(j-1)} \quad j=1...N-2 \tag{8}$$

$$C_i^3(r)=\sum d_{ij}\cap d_{(i-1)(j-1)}\cap d_{(i-2)(j-2)} \quad j=1...N-2 \tag{9}$$

Obviously, the value of the estimate depends on m and r. As suggested by Pincus, m can be taken as 2 and r as (0.1–0.25) SD, where SD is the standard deviation from the original data sequence. As a rule, in engineering practice, more than 100 data are needed to meet the requirements for estimating a robust value of ApEn. Consequently, in this paper the ApEn is calculated under the following conditions:

$$N\ge 100, r=0.15SD, m=2.$$

2.3. The Calculation of Approximate Entroy Algorithm Properties

Definition 1: The ApEn values have just as much periodic to original signal.

Proof: If we now define $f(x)$ as a periodic function with a period T,

$$f(x+T)=f(x) \tag{10}$$

Then,

$$ApEn(f(x+T))=ApEn(f(x)) \tag{11}$$

The vector $ApEn(f(x+T))$ show the periodic intensity modulation in the chaos domain. Also, the maximum and minimum of ApEn values are shown in a sameperiodic property.

$$Max\left(ApEn(f(x+T))\right)=Max\left(ApEn(f(x))\right) \tag{12}$$

$$Min\left(ApEn(f(x+T))\right)=Min\left(ApEn(f(x))\right) \tag{13}$$

Definition 2: The new system consists of a stable system is not necessarily stable.

System A and System B are stable system. When the system A is converted into system B, system A will not always in a stable state.

Proof:

If,

$$y(n)=2\sin(0.2n)+1 \quad 1\le n\le 500 \tag{14}$$

$$z(n)=1.5\sin(0.2n)+2\cos(0.5n)-0.2, \quad 1\le n\le 500 \tag{15}$$

$$f(n)=\left\{\begin{matrix}z(n) & 1\le n\le 500\\ y(n) & 500<n\le 1000\end{matrix}\right\} \tag{16}$$

$$S_A=ApEn(y(n)) \tag{17}$$

$$S_B = ApEn(z(n)) \quad (18)$$

$$S_f = ApEn(f(n)) \quad (19)$$

As seeing from Figure 1b and Figure 2(b):

$$S_A < S_B \quad (20)$$

Then,

$$ApEn(f(n)) < ApEn(z(n)), n \in [400, 500] \quad (21)$$

The new system $f(n)$ is not always in a stable state,see in Figure 3.

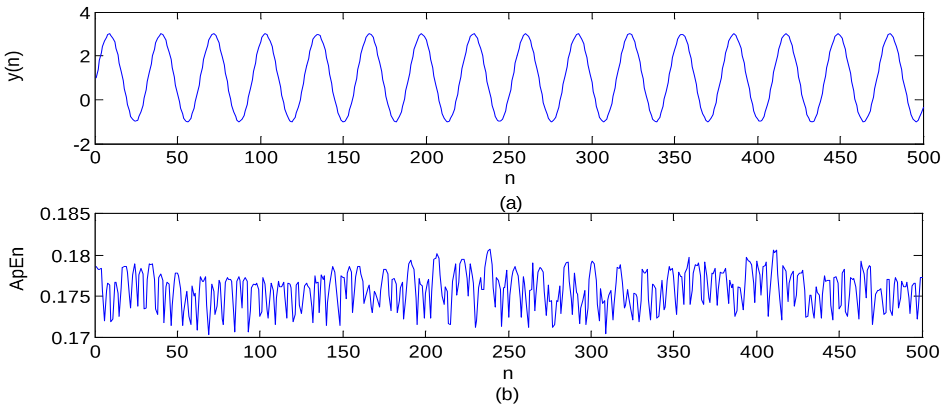

Figure 1. (a)The Time Series of Equation14; (b) the ApEn of (a)

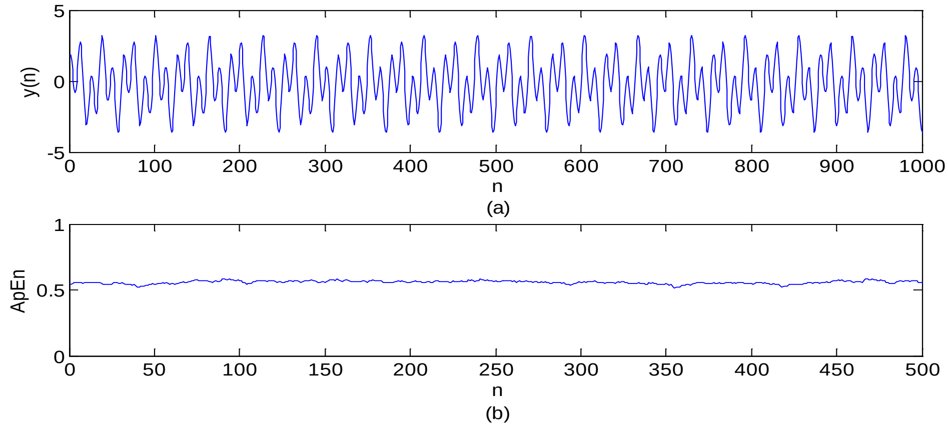

Figure 2. (a)The Time Series of Equation15; (b) the ApEn of (a)

Definition 3: Any signal can be reconstructed by sinusoidal function.
Proof: If we now define $f_T(t)$ as a periodic function with a period T,

$$\lim_{T \to \infty} f_T(t) = f(t) \quad (22)$$

The single sinusoid $g(t)$ is defined as:

$$g(t) = A\sin(2\pi\varpi t + \varphi) \tag{23}$$

The parameters in Equation 23 are the amplitude A ,the frequency ω and phase ϕ. It was Fourier's hot idea to consider a sum of sinusoids as a model for $f(t)$ distribution.

$$f(t) = A_0 + \sum_{n=1}^{\infty} A\sin(n\varpi t + \varphi_n) \tag{24}$$

Any signal can be reconstructed by sinusoidal function.

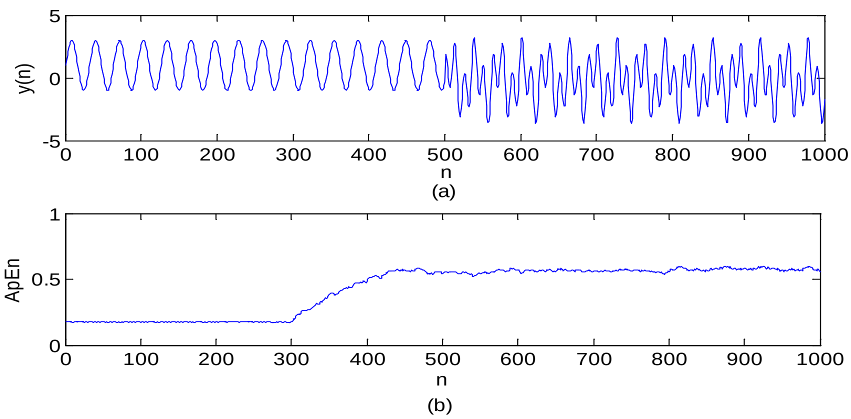

Figure 3. (a) The Time Series of Equation16; (b) the ApEn of (a)

Definition 4: A breakdown of the system point mutation into the system B,the burst point flag ApEn value is defined as:

$$\psi = 0.2 \tag{25}$$

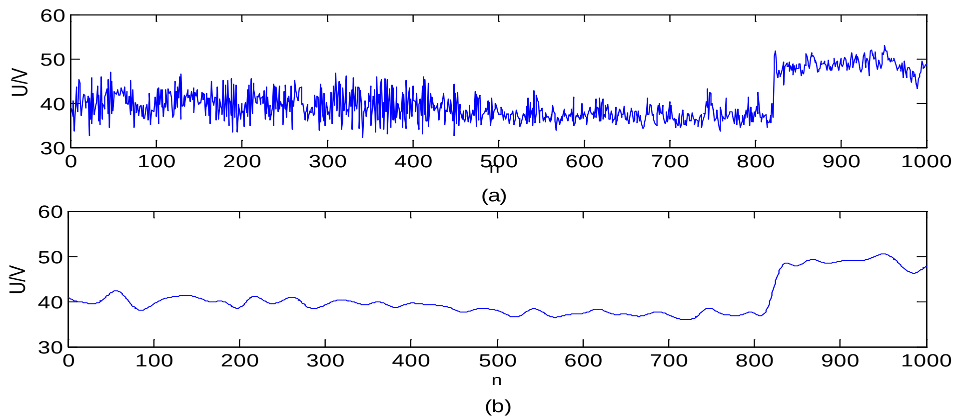

Figure 4. Extract Waveform of arc Withwavelets Algorithm. (a) Original Arc; (b) the Denoise with Wavelets Algorithm of (a)

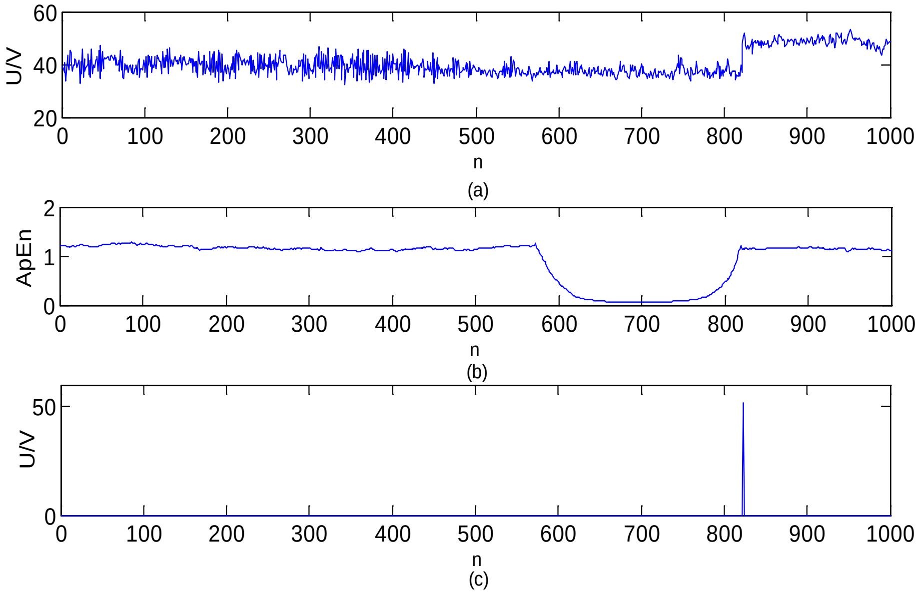

Figure 5. Get the Burst Point. (a Original Arc;(b)the ApEn of (a); (c)the burst point of (a)

3. Results and Analysis

3.1. Comparative Analysis of Algorithms

Wavelet algorithm,MC-ApEn algorithm (moving cut data approximate entropy), BD-ApEn (Burst detection data approximate entropy)algorithm are high-power welding arc signal Figure 4a, Figure 5a analysis.

Wavelet analysis method to eliminate signal noise, accurate waveform feature extraction as illustrated in Figure 4b.

A vector that denotes the magnitude and direction of weld arc, is reconstructed MC-ApEn algorithm,as illustrated in Figure 5b.

BD-ApEn algorithm not only reconstructe A vector that denotes the magnitude and direction of weld arc,but also extract burest point,as illustrated in Figure 5c.

3.2. The influence of the phase space size for the classification

Here,we select a fault arc data, shown in Figure 6a, and then fixe the different sizes of phase space D, respectively D=50, D=150, D=250, D=350, D=450, calculate its approximate entropy in phase space.

Fixed D=50, approximate entropy drill-down to zero,and the approximate entropy gap dislocation, see in Figure 6b. The size of phase space is increased sufficiently to 150 and there is a clear approximate entropy concave gap, see in Figure 6c. Then, the scanning range is increased sufficiently to 250, and the gap dislocation would come even soonerin Figure 6c. Finally, the size of phase space is increased again to D=350, the form of approximate entropy become further smother, see in Figure 6(e).

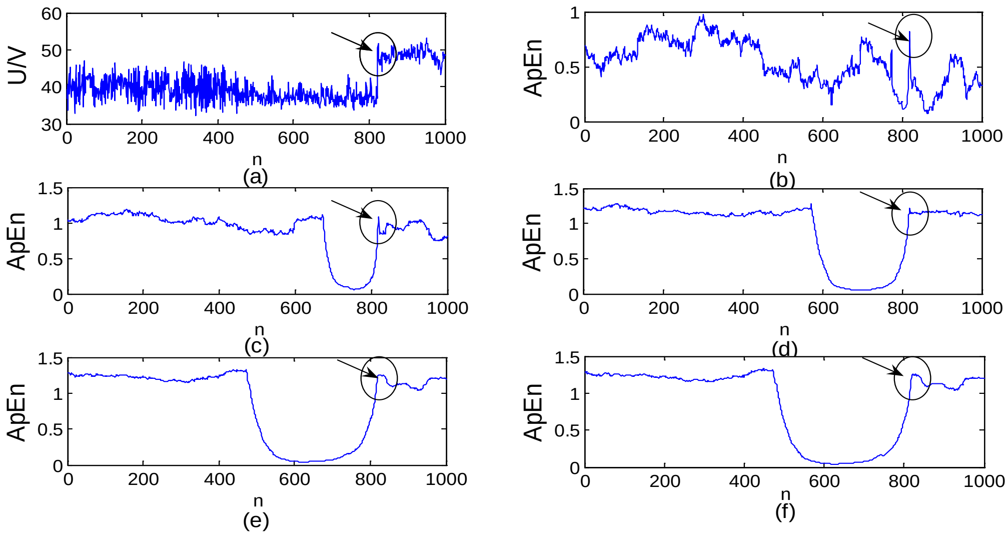

Figure 6. (a) original arc; (b) the ApEn of (a) where D=50;(c)the ApEn of (a) where D=150; (d) the ApEn of (a) where D=250; (e) the ApEn of (a) where D=350; (e) the ApEn of (a) where D=400

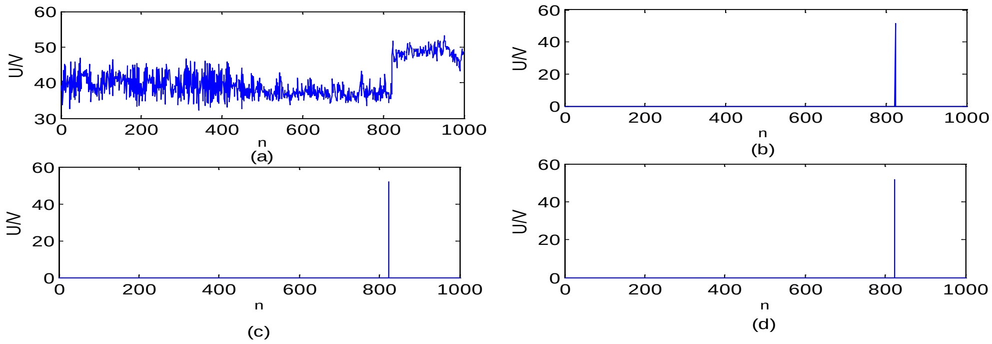

Figure 7. (a) original arc; (b)the burst point of (a) where D=150; (c) the burst point of (a) where D=250; (d) the burst point of (a) where D=350

Experimental results show algorithm is robust to calibrate the singularity points and denote the kinetics and stability of arc, see Figure 7.The resolution and separation efficiency were improved greatly by regulating the sizes of phase space. The larger of phase space , The hole of arc is more obvious and vice versa. In practice, the effect of phase space will be considered.

4. Conclusion

In essence, the method of digital filtering is used first, and then restored to its original feature. However, it is unable to denotes the non-linear dynamical features. The calculation of the approximate entropy in phase space,which is different from wavelet signal detection method,will not only calibrate the singularity points but also denote the kinetics and stability of arc. A vector, which is with the calculation of the approximate entropy in phase space,denotes the distortion of arc. The calculation of the approximate entropy in phase space, which is a complexity measure suitable for short data, evolve as a problem-state monitoring system.

Acknowledgements

This work was supported by pdjh2016b0752,2014ZJ002.

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