Defection Recognition of Cold Rolling Strip Steel Based on ACO Algorithm with Quantum Action

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Abstract. To enhance plate quality of cold rolling strip steel, a method based on Ant Colony Optimization with Quantum Action (ACO-QA) is developed. In this method, each ant position is represented by a group of quantum bits, and a new quantum rotation gates are designed to update the position of the ant. In order to makes full efficiency, a pretreatment using fuzzy method is firstly adapted before resolving the mathematical model with ACO-QA. This method overcomes the shortcoming of ACO, which is easy to fall into local optimums and has a slow convergence rate in continuous space. At last, a field cognition system is designed to test the efficiency of this method. The results show that it can validly identify almost all defection patterns, compared to traditional identification system. The recognition precision of this method is higher and can meet the shape recognition requirements of cold rolling strip steel.

Keywords: defection recognition, cold rolling, ACO, quantum calculation.

1 Introduction

In recent years, the production technology of cold rolled strip steel has progressed greatly at home and abroad. Surface flatness degree is an important quality indicator of cold rolled strip steel. And the shape control has become a hot topic of cold rolling process [1, 2]. Therefore, the strip shape recognition is an important part in control of strip steel rolling process, while only strip shape checked online is identified as controllable defect mode, can we effectively determine precise adjustment of the shape control implementing agencies, thereby producing high-quality steel strip products.

With the development of the strip shape control, there appears some shape cognition methods [3, 4]. Polynomial Regressive Solution (PRS) and Orthogonal PRS are the conventional two. However, the PRS and O-PRS have so bad noise immunity that they only can deal with simple shape deformation and cannot meet the requirement of high precision. Moreover, fuzzy classification and manual neural network (ANN) is used recently [5, 6]. The former is simple and practical while its ability of cognition and precision are inferior to the latter. ANN method allows the measured signal rather large errors and it can magnify the key ingredients and

Z. Pan et al. (Eds.): Transactions on Edutainment VII, LNCS 7145, pp. 263–271, 2012.

depresses the secondary ones. However, the single use of ANN needs to operate on original target image and makes classification directly so that it hinders the accuracy and decrease the velocity of the cognition procedure [7, 8].

In this paper, Legendre polynomial expression is used for description the basic mode of strip shape defections, and its linear combination presents any shape signal model. Based on fuzzy pattern recognition, an improved ant colony optimization methods with quantum solution[9-12] is adapted, reducing the dimension of the solution and the search space, thereby increasing the accuracy and speed of recognition, meeting the high precision shape control requirements.

2 Signal Mathematical Model of the Shape

2.1 Normalization

Due to the factors of mechanical or the heat roller deformation, the metal extends non-uniformly down the width direction when the strip steel being cold rolled, thereby causing different patterns of plate defects. Usually we take the horizontal tension distribution of the strip as the flatness signal σ_i, which is measured by the sensor and needs to be normalized:

$$\Delta\sigma_i = \frac{\sigma_i'}{\max|\sigma_i'|} \qquad (i = 1, 2, ..., n) \tag{1}$$

Where, $\sigma_i' = \sigma_i^R - \sigma_i^T$, $\sigma_i^R = \sigma_i - \overline{\sigma_i}$, σ_i' represents the flatness deviation, σ_i^T represents the stress of the flatness, σ_i^R represents the actual residual stress, and $\overline{\sigma_i}$ represents the average flatness stress by measurement or calculation.

2.2 Signal Description

According to the technique of manipulated rolling mill, the process facts and control requirements, the 6 adjustable simple plate defects (Fig.1)

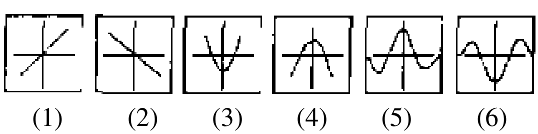


Fig. 1. Six basic shapes: (1) left plat-profile, (2) right plat-profile, (3) middle plat-profile, (4) bilateral plat-profile, (5) quarter plat-profile and (6) side-middle plat-profile

Legendre polynomials are usually used to describe the corresponding residual stress distribution of the above 6 basic standard models. If $\sigma^{(k)}$ represents the sample of normalized standard defects of flatness (k=1, 2… 6), then the standards-based equations of the above six version are as follows:

$$\sigma^{(1)} = p_1(x) = x \tag{2}$$

$$\sigma^{(2)} = -p_1(x) = -x \tag{3}$$

$$\sigma^{(3)} = p_2(x) = 3x^2/2 - 0.5 \tag{4}$$

$$\sigma^{(4)} = -p_2(x) = -(3x^2/2 - 0.5) \tag{5}$$

$$\sigma^{(5)} = p_4(x) = (35x^4 - 30x^2 + 3)/8 \tag{6}$$

$$\sigma^{(6)} = -p_4(x) = -(35x^4 - 30x^2 + 3)/8 \tag{7}$$

Usually the flatness of the strip steel can be expressed by a linear combination of the basic mode flatness signal:

$$\Delta\sigma(x) = \alpha p_1(x) + \beta p_2(x) + \gamma p_4(x) \tag{8}$$

2.3 Mathematical Model

Given signal samples $\sigma(x_i)$, $i = 1, 2, \ldots, n$, we get the target function:

$$\min f = \sum_{i=1}^{n} \left| \Delta\sigma_i - \alpha p_{1i} - \beta p_{2i} - \gamma p_{4i} \right| \tag{9}$$

The processes of the flatness signal pattern recognition is to evaluate the flatness characteristics of α , β and γ to make f minimum.

3 ACO-QA Algorithm

3.1 Fuzzy Pretreatment of the Objective Function

The mathematical model of flatness signal recognition is a non-convex nonlinear equation, which is difficult to get solution directly. To reduce the solving difficulties and improve recognition efficiency, fuzzy pretreatment is first used.

Suppose that $\omega(x_i)$ satisfies the normalization qualification, $\sum_{i=1}^{n} \omega(x_i) = 1$, $X = \{x_1, x_2, \ldots, x_n\}$, some definitions are given as follows:

i) The weighted Hamming distance between the standard signal $\sigma^{(k)}$ and the flatness signal to be solved:

$$H_\omega(\Delta\sigma,\sigma^{(k)}) = \sum_{i=1}^{n} \omega(x_i)(\Delta\sigma(x_i) - \sigma^{(k)}(x_i)) \tag{10}$$

ii) The closeness of the weighted Hamming distance between the standard sample and the sample to be solved:

$$D(\Delta\sigma,\sigma^{(k)}) = \sum_{i=1}^{n} \omega(x_i)(1 - \left|\Delta\sigma(x_i) - \sigma^{(k)}(x_i)\right|) \tag{11}$$

iii) The $P_E(K)$ represents the fuzzy degree of samples belongs to K class, that is, the similarity of samples for K class:

$$P_E(K) = E(K) / \sum_{K=1}^{N} E(K) . \tag{12}$$

Where,

$$E(K) = \begin{cases} D(i) - D(i+1) & D(i) > D(i+1) \\ 0 & D(i) < D(i+1) \end{cases} . \tag{13}$$

Then, we take the minimum error between the fuzzy identification result and measured results as the objective optimizing function:

$$\min f(x) = \min f(x_1, x_2, \ldots, x_n) = \sum_{i=1}^{n} \left| \sum_{k=1}^{3} P_E(K)\sigma_i^{(k)} - \Delta\sigma_i \right| \tag{14}$$

3.2 Quantum Optimization Algorithm Based on ACO

Generate Initial Population. In the ACO-QA, the probability amplitude of quantum bits is directly taken as the ants' current location encoding:

$$q_i = \left[\begin{vmatrix} \cos(\theta_{i1}) \\ \sin(\theta_{i1}) \end{vmatrix} \begin{matrix} \cos(\theta_{i2}) \\ \sin(\theta_{i2}) \end{matrix} \begin{vmatrix} \cdots \\ \cdots \end{vmatrix} \begin{matrix} \cos(\theta_{in}) \\ \sin(\theta_{in}) \end{matrix} \right| \right] \tag{15}$$

Where, $\theta_{ij} = 2\pi \times rnd$, the *rnd* is a random number between 0 and 1, i=1,2,…,m, j=1,2,…n. And m is the population size, n is the space dimension.

The definition domain of variable X_i is $[a_i,b_i]$. Note quantum bits j of ant q_i as $[\cos\theta_{ij}, \sin\theta_{ij}]^T$,then the corresponding solution space variables are:

$$\begin{bmatrix} p_{i0}^j \\ p_{i1}^j \end{bmatrix} = \begin{bmatrix} \frac{b_i - a_i}{2} & 0 \\ 0 & \frac{b_i - a_i}{2} \end{bmatrix} \begin{bmatrix} \cos\theta_{ij} \\ \sin\theta_{ij} \end{bmatrix} + \begin{bmatrix} \frac{b_i + a_i}{2} \\ \frac{b_i + a_i}{2} \end{bmatrix}$$

Simplify the above formula:

$$\begin{bmatrix} p_{i0}^{j} \\ p_{i1}^{j} \end{bmatrix} = \frac{1}{2}\begin{bmatrix} 1+\cos\theta_{ij} & 1-\cos\theta_{ij} \\ 1+\sin\theta_{ij} & 1-\sin\theta_{ij} \end{bmatrix}\begin{bmatrix} b_i \\ a_i \end{bmatrix} \tag{16}$$

Update Ants' Location. In the ACO-QA, firstly transform the increment of pheromone strength in the path of the ants in general ACO into rotation angle updates of quantum rotation gate; then update qubits carried by ants through the quantum rotation gate; therefore, the update of the ants location is converted to the update of probability amplitude of the ant qubit.

Adjust the Angle Size and Direction of Quantum Rotation Gate. Usually update the qubit with the rotation gate $U(\Delta\theta) = \begin{bmatrix} \cos(\Delta\theta) & -\sin(\Delta\theta) \\ \sin(\Delta\theta) & \cos(\Delta\theta) \end{bmatrix}$.

The following angle step function is put forward to ascertain the size of angle:

$$\Delta\theta_{ij}(t+1) = -\mathrm{sgn}(A)(\Delta\theta_{ij}(t) + c_1\Delta\tau_{Lij}(t) + c_2\Delta\tau_{Gij}(t)), \tag{17}$$

$$\Delta\tau_{Lij}(t) = \sum_{k=1}^{m}\frac{Q}{d_{ij}} , \tag{18}$$

$$\Delta\tau_{Gij}(t) = \sum_{k=1}^{m}\frac{Q}{L_k} . \tag{19}$$

Where, c_1 and c_2 represent the local adjustment factor and the global adjustment factor of the pheromone strength respectively, Q is the pheromone strength, L_k represents the total length of the path that the ant K goes through in this cycle, d_{ij} represents the distance of the path ij that the ant K passes by, and $\Delta\tau_{Lij}(t)$ represents the variation of the global pheromone, $\Delta\tau_{Gij}(t)$ represents the variation of the local pheromone.

Mutation of the Ant Position. Given the mutation rate p_m, assign each ant a random number $rand_i$ between 0 and 1. If $rand_i < p_m$, randomly select $n/2$ quantum bits of the ant, then exchange two probability amplitude with two quantum non-gate, and the optimal position remains :

$$\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}\begin{bmatrix} \cos(\theta_{ij}) \\ \sin(\theta_{ij}) \end{bmatrix} = \begin{bmatrix} \sin(\theta_{ij}) \\ \cos(\theta_{ij}) \end{bmatrix} = \begin{bmatrix} \cos(\theta_{ij}+\pi/2) \\ \sin(\theta_{ij}+\pi/2) \end{bmatrix} . \tag{20}$$

Where, $i \in \{1,2,\cdots,m\}$ and $j \in \{1,2,\cdots,n\}$.

3.3 Algorithm Steps

Suppose that there are *m* ants in three-dimensional space, and the coordinate of each ant is $x_{id} = (x_{i1}, x_{i2}, x_{i3})(d = 1,2,3)$. The corresponding characteristic parameters of flatness to be recognized is (α, β, γ), and note x_{pi} as the best position that ant *i* goes by and x_g as the best position that the ant colony. Algorithm steps are as follows:

Step1. Ant population initialization. Generates ants locations according to Eq (15) to compose the initial population. The initial value of three positions for each ant corresponds to the three non-zero value $P_E(K)$ of fuzzy pretreatment.

Step2. Get solution *P* (*t*) according to Eq(16) and calculate the fitness of each ant according to the specific optimized objective function:

$$\min f(x) = \min f(x_1, x_2, \ldots, x_n) = \sum_{i=1}^{n} \left| \sum_{k=1}^{3} P_E(K)\sigma_i^{(k)} - \Delta\sigma_i \right|.$$

If the ant's the current location is better than their own optimal position in memories, then replace with the current location; if the current global best position is better than that before, then replaced with the current global best position.

Step3. Complete the update of the ant location according to Eq(17), (18), and (19).

Step4. With mutation probability, do mutation operation for each ant according to Eq(20).

Step5. Back to Step2 until meeting with the convergence criteria or reaching the upper bound of generation. Output current location coordinates of the ant.

Step6. End. Return to the current global optimum value x_{id}, and the corresponding three locations (x_{i1}, x_{i2}, x_{i3}), that is, the flatness characteristic parameters (α, β, γ).

4 Experiment and Results Analysis

4.1 System Structure

A typical system designed in Chongqing University Automation Lab is shown in Fig.2. Bus adopts standard VME structure and image collection uses standard linear array scanner with 2048-4096 pixels and more than 10 kHz frame rate. Considering system transacting ability and present ADC's rate, ADS851(40MSPS/14bit) is an appropriate option. Light source we use is high strength strobotron lamp.

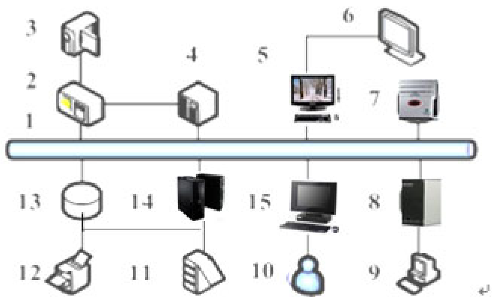


Fig. 2. Structure of cold rolling steel strip visualization detecting system: 1 VME Bus, 2 DSP, 3 CCD, 4 automatic classifier (optional), 5 image showing system, 6 operator monitor, 7 system main controller, 8 net interface, 9 quality control computer, 10 keyboard, 11 data storage system, 12 printer, 13 data analysis module, 14 file and figure management system, and 15 man-machine interface

4.2 Optic Setting

As Fig.3 shows, the light path of CCD adopts telecentric type which can improve measure sensitivity because it enables the CCD focal plane and the steel strip plane superposed.

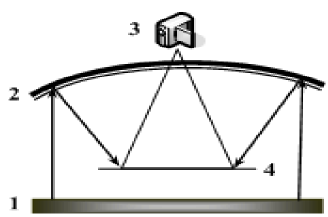


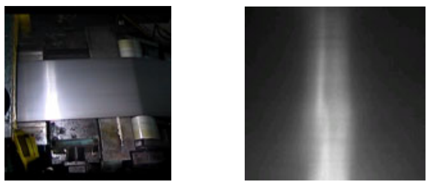
Fig. 3. Telecentric optical system. In this system, 1 is the cold rolling steel strip, 2 is the concave mirror, 3 is CCD and 4 is the plane mirror.

4.3 Field Conditions

Some important parameters used in field experiments are listed in Table 1 and Fig.4 is an instantaneous photograph from CCD video.

Table 1. Some important field parameters

Item	Value
Height of CCD positioned	3.8m
Width of steel strip	1039.8mm
Velocity of steel strip	0.740m/s
Size of image collected(pixel*pixel)	340*768
Frequency of strobotron lamp	12HZ



(a) (b)

Fig. 4. Images of work field. It gives site screenshot from video collected by CCD. (a) is the snapshot image from CCD and (b) is the focus part of this image.

4.4 Experimental Results

In pattern recognition field, fuzzy technology and neural network are two important methods, which are used popularly and effectively in many fields. Therefore, experiment uses them to compare with the proposed method ACO-QA in this paper. Experimental results (Table 2) show that the recognition accuracy using ACO-QA is higher than fuzzy method and neural network method.

Table 2. Result comparisons between several different algorithms

Defect Type	Fuzzy Method	NN Method	ACO-QA
(1)	82%	87%	90%
(2)	80%	85%	88%
(3)	81%	86%	91%
(4)	79%	83%	86%
(5)	84%	88%	91%
(6)	83%	86%	89%
Average Accuracy	82%	85%	89%

In Table.2, (1) represents the case of left plat-profile, (2) the right plat-profile, (3) the middle plat-profile, (4) the bilateral plat-profile, (5) the quarter plat-profile, and (6) the side-middle plat-profile.

5 Conclusions

Legendre function is firstly used to describe six kinds of basic shape defects of cold rolled strip steel, which has only three dimensions. Then a method based on novel ant colony optimization algorithm with quantum evolutionary action (ACO-QA) is developed for shape recognition of cold rolled strip steel. Because ACO-QA has an optimal effect almost in low-dimensional and low-interval case, this recognition method loads a pretreatment of fuzzy pattern recognition to the initial shape identification, thereby improves identification accuracy and efficiency of the cold rolled steel strip shape.

Acknowledgments. This work is supported by a Grant for Research Projects of Science and Technology Division from Chongqing Scientific and Technological committee (CSTC2009AC2068) and another Grant for Science Research Starting Projects from Chongqing University of Technology (2008ZD24).

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