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Fuzzy Pattern Recognition in Atlas and Images of the Unevenness of Carbide in Tool Steel

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Abstract: Fuzzy pattern recognition has been employed to identify some atlas and images of the unevenness of carbide in tool steel. Three models have been constructed. These models were based on fuzzy mathematics theory, as well as fuzzy pattern recognition method. Distribution rule of the unevenness of eutectic carbide in ledeburite steel is proposed in these models respectively.

Key words: fuzzy mathematics; fuzzy and pattern recognition; characteristic; specimen

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Ledeburite steel is usually used to make die and special bearing, for it is various and abundant. The unevenness of eutectic carbide is acted as an important index to determine the quality of steel products, especially in the classifying by microscopic structure. Since the distribution is uneven and irregular, it is very difficult to digitize the quantity of carbide in steel. Therefore, it is classified mainly by manual work. If a feasible automatic classification method is set up, it will be more convenient and beneficial to the producing progress. Digital image equipment and computer technology can be utilized to classify the carbide in steel products automatically, but it is hard to apply classic mathematics in quantitative analysis. Fuzzy sets theory is practicable to overcome the problem [1–3].

1 Fuzzy Description of the Unevenness of Carbide

Dot-matrix characters (such as hieroglyph, bar code and etc.) are often served in computer I/O device [4, 5]. The characters can be divided into small pane ($m\times n$). The image element should be black, white, or black and white. The image can be sampled discretely in the digitization progress by a software named Image-Pro.

A digital image is a discrete image both in spatial coordinate and brightness, which can be described by the sampled data. To facilitate the calculation, we use the coordinate (x, y) to express each pixel. In addition, the brightness of image is represented by membership function $f(x, y)$. Therefore, each pixel is described by a group of data $(x, y, f(x, y))$.

2 Construction of Models

2.1 The fuzzy recognizable model

Definition 1 $\sigma(A, B)$ is the affinity between A and B, if mapping σ: $\boldsymbol{m}_{n\times 1}\times\boldsymbol{m}_{n\times 1}\to[0,1]$, $(A,B)\mapsto\sigma(A,B)$, and the following condition is satisfied:

(1) $\sigma(A,B)=\sigma(B,A)$;

(2) $\sigma(A,B)=1\Leftrightarrow A=B$;

(3) $\sigma(E,O)=0$;

(4) $A\subseteq B\subseteq C\Rightarrow\sigma(A,C)\le\sigma(A,B)\wedge\sigma(B,C)$.

Definition 2 Let "*" be an operator, $\forall R\in\boldsymbol{m}_{n\times 1}$, $\forall S\in\boldsymbol{m}_{n\times m}$, $*(R, S)=R*S=(R^cS)^c\in\boldsymbol{m}_{m\times 1}$, where R^c is the transpose of R.

Theorem 1 Suppose $Q=(q_i)_{n\times 1}\in\boldsymbol{m}_{n\times 1}$ is a fixed column vector, and $\sum\limits_{i=1}^{n}q_i^2=a$, $R=(r_{ij})_{n\times m}$, $S=(s_{ij})_{n\times m}$, let $\Phi(Q*R, Q*S)=1-\frac{1}{\sqrt{an}}\sqrt{\sum\limits_{i=1}^{n}\sum\limits_{j=1}^{m}(q_ir_{ij}-q_is_{ij})^2}$, then Φ is an affinity function.

Definition 3 Quad-structure [6, 7] $P=(p(U), \boldsymbol{m}_{m\times 1}, \tilde{T}\circ T, \Phi)$ is defined as a fuzzy recognized space which composed by $p(U)$, $\boldsymbol{m}_{m\times 1}$, $\tilde{T}\circ T$, Φ.

Where $p(U)$ is the power set constituted by all subsets of point set U of two-dimensional space; $\boldsymbol{m}_{m\times 1}$ is set of all fuzzy matrix; T is mapping from $p(U)$ to $\boldsymbol{n}_{n\times 2}$; $\tilde{T}$ is fuzzy mapping from $\boldsymbol{n}_{n\times 2}$ to $\boldsymbol{m}_{m\times 1}$; Φ is affinity function.

Law of discrimination

Suppose $A_1, A_2\cdots, A_n, B\in p(U)$, where $A_1, A_2\cdots, A_n$ are patterns, B is an undetermined sample.

Suppose $(\tilde{T}\circ T)(A_i)=A_i$, $A_i\in\boldsymbol{m}_{m\times 1}$, $(i=1, 2, \cdots, n)$, $(\tilde{T}\circ T)(B)=B$, $B\in\boldsymbol{m}_{m\times 1}$, if $\Phi(Q*A_i, Q*B)=\max\{\Phi(Q*A_1, Q*B), \Phi(Q*A_2, Q*B), \cdots, \Phi Q*A_n, Q*B)\}$, then B is the closest sample to pattern i.

2.2 Fisher model

Fisher model is a distinguishing method based on fuzzy pattern recognition, which can convert a nonlinear system to a linear one.

Suppose that N samples $x_1, x_2, \cdots, x_N$ (x_i is a n-dimensional vector, $i=1,2,\cdots,N$) are included in a set. These samples have been clustered c types. Type i is marked as X_i ($i=1,2,\cdots,c$). In addition, suppose that type i include n_i samples.

Law of discrimination

For an arbitrary undetermined sample (d-dimension space) $Z=\{z_1, z_2, \cdots, z_t\}$.

(1) Calculate the mean value of the undetermined sample

$$m=\frac{1}{t}\sum_{i=1}^{t} z_i;$$

(2) Calculate the discrete matrix constructed by each pattern and the undetermined sample

$$s_b^{(i)}=(m_i-m)(m_i-m)^c,\ i=1,2,\cdots,c.$$

Where m_i is the mean value of X_i, $(m_i-m)^c$ is the transpose of (m_i-m);

(3) Calculate the discrimination function

$$J_b^{(i)}=\mathrm{tr}(|S_b^{(i)}|)=\sum_{i=1}^{d}\lambda_i,$$

where $\mathrm{tr}(|S_b^{(i)}|)$ is the trace value of the determinant $|S_b^{(i)}|$;

(4) Discriminate the type of the undetermined sample Z

$$J_b^{(i)}=\min\{\mathrm{tr}(|S_b^{(1)}|), \mathrm{tr}(|S_b^{(2)}|), \cdots, \mathrm{tr}(|S_b^{(c)}|)\}.$$

2.3 The multi-element fuzzy pattern recognizable model

The multi-element fuzzy pattern recognition model [8] is based on fuzzy mathematics. It is a multi-characteristic pattern recognition method. In this paper, the mean, variance, coefficient of variation, root mean square value, and homogenization of the undetermined sample are regarded as the character.

(1) Mean (the variation of static component of images are reported by mean)

$$\bar{x}=\frac{1}{N}\sum_{i=1}^{n} x(i);$$

(2) Variance (the variation of dynamic images are reported by variance)

$$\sigma_x^2=\frac{1}{N-1}\sum_{i=1}^{N}(x(i)-\bar{x})^2.$$

From the description, we can conclude that the larger value of σ_x^2, the more uneven distribution of the images, and the more variation of the value of $x(i)$;

(3) Coefficient of variation (the smoothness of the images are reported by the coefficient of variation)

$$c_x=\frac{\sigma_x}{\mu_x}=\frac{\sigma_x}{\bar{x}}=\frac{\sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x(i)-\bar{x})^2}}{\bar{x}}=\frac{\sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x(i)-\bar{x})^2}}{\frac{1}{N}\sum_{i=1}^{N}x(i)};$$

(4) Root mean square value (the energy variation of the images are reported by root mean square value)

$$V_{\max}^2=\frac{1}{N}\sum_{i=1}^{N}x^2(k);$$

(5) Homogenization (the data skip degree of the images are reported by homogenization)

$$l=\frac{\text{the minimum of } f(x,y) \text{ in square travelling frame}}{\text{the maximum of } f(x,y) \text{ in square travelling frame}}.$$

Law of discrimination

For an undetermined sample, we definite the membership function between the pattern and the undetermined sample on the basis of mean, variance, coefficient of variation, root mean square value, and homogenization.

$$\underset{\sim ij}{A}(x)=\begin{cases}1-\frac{(x_{sy_i}-x_{bt_i})^2}{\sigma_{bt_i}^2}, & |x_{sy_i}-x_{bt_i}|\le\delta_j\\ 0, & |x_{sy_i}-x_{bt_i}|>\delta_j\end{cases},$$

where $i=1,2,\cdots,c$, $j=1,2,\cdots,5$; $\underset{\sim ij}{A}(x)$ is the membership function of pattern X_i on the character j;

$$\bar{x}=\frac{1}{N}\sum_{i=1}^{n}x(i);$$

x_{sy_i} is the value of undetermined sample on character j; x_{bt_i} is the value of pattern on character j; σ_{bti}^2 is the variance of the pattern mode i; δ_j is a constant.

Suppose $s_i=\min\{\underset{\sim i1}{A}(x), \underset{\sim i2}{A}(x), \underset{\sim i3}{A}(x), \underset{\sim i4}{A}(x), \underset{\sim i5}{A}(x)\}$,

if $s_{i0}=\max\{s_1, s_2, \cdots, s_{11}\}$, then the undetermined sample is most closed to pattern i_0. That is to say, the undetermined sample belongs to type i_0 ($i_0\in\{1,2,\cdots,c\}$).

3 Application and Examination of Models

According to the method of the three models, the program can be designed to recognize the tool steel carbide images. The results are as following (**table 1**).

4 Conclusions

(1) From table 1, the recognition accuracy of the first model is best, 83%; the second is better, 65%; the third is not good, only 43%.

(2) The recognition velocity of the first is slow. It needs 7 s to recognize a sample. The second and the third need only 0.5 s. The deviation is 14 s.

(3) We will make the first model better, aimed at im-

Table 1 Comparison of calculating results of three models and rating for manual work

Number of the undermined samples	Results of manual work*	Fuzzy recognizable model		Fisher model		Multi-element fuzzy pattern recognizable model	
		Result	Conformity	Result	Conformity	Result	Conformity
1	1	1	✓	1	✓	4w (4-level net)	×
2	1	1	✓	1	✓	4d (4-level strip)	×
3	1	1	✓	1	✓	3	×
4	1	1	✓	2	×	4d	×
5	1	1	✓	1	✓	3	×
6	4d	4d	✓	4d	✓	4w	×
7	4d	4d	✓	4d	✓	4d	✓
8	4d	4d	✓	4d	✓	1	×
9	2	2	✓	3	×	4w	×
10	2	2	✓	4d	×	3	×
11	3	3	✓	5w	×	5w	×
12	2	2	✓	4d	×	3	×
13	3	3	✓	4d	×	5w	×
14	3	4d	×	4d	×	5w	×
15	3	3	✓	4d	×	5w	×
16	5w	5w	✓	5w	✓	5d	×
17	5w	3	×	5w	✓	5w	✓
18	5w	3	×	5w	✓	5w	✓
19	5w	3	×	5w	✓	5w	✓
20	5w	5w	✓	5w	✓	5w	✓
21	5w	5w	✓	5w	✓	5w	✓
22	5w	5w	✓	5w	✓	5d	×
23	5w	5w	✓	5w	✓	5w	✓
Accuracy		83%		65%		43%	

Note: * is based on the pattern evaluation of GB1299-85; ✓ is conformity, × is unconformity.

proving the accuracy, especially the speeding. In addition, we will revamp the second model and the third model, not only on the method, but also on the accuracy.

Because the photos of the patterns and the undetermined samples are taken at different institution, and the dust on the surface of the undetermined sample is not detected, there are some errors in the results.

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