Image analysis of high temperature melting process of iron tailings based on clustering model

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Abstract: In this paper, the melting process of iron tailings was studied. The region of silicon dioxide was obtained from 140 sequence images of silicon dioxide in high temperature molten pool during the melting process. According to the clustering results, the number of pixels in the whole image and the intercepted iron tailings image is counted. The specific physical process is analyzed by combining the pixel number of the whole image and the crucible outer diameter data. In this paper, the piecewise function and the exponential function of the angle between the center of mass and the center of the crucible are established. The position of the mass center and its motion track are studied, and the track diagram of the two-dimensional space is drawn by MATLAB. The morphology and area of SiO2 in the melting process can be effectively described by using the generalized diameter method. The phase between the generalized diameter and the velocity is calculated by using the micro element method. The melting rate at different time was quantitatively characterized by correlation function. The research realizes the transformation of data information from complex melting process to its change law, establishing reliable time sequence law for high temperature melting process, providing strong theoretical basis for production practice, and avoids various losses caused by repeated tests to a certain extent.

1. Introduction

High value-added thermal insulation materials can be prepared by direct fiber forming process of quenched and tempered blast furnace slag, which can efficiently utilize the sensible heat of slag which has not been used at present. However, it is difficult to test many physical parameters due to the high temperature in the direct fiber forming process of blast furnace slag. Li Xiaobing and others studied the dissolution process of MgO and obtained the influence rules of slag composition and reaction temperature on the dissolution behavior of MgO, but repeated experiments were inefficient[1-3]. Liu Yifan obtained the time sequence of the dissolution process by non-contact method, but only obtained the relationship between the change of slag area and time[4].

At present, most of the researches focus on experimental determination, which requires high experimental requirements and is difficult to operate. In this paper, the piecewise function and the angle exponential function of the distance from the center of mass to the center of the crucible are proposed, which the movement track of dissolved mass center of iron tailings is measured. The morphology and area of iron tailings in the melting process is measured by generalized diameter method, and the melting rate at different times is quantitatively characterized by micro element method. Based on computer vision and mathematical model, the dynamic physical information of iron tailings melting at high temperature can be obtained. To a certain extent, it provides theoretical and technical support for the direct fiber forming process of blast furnace slag.

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2. Basic theoretical model

The main component of iron tailings is silica, which is the most difficult part to melt. Therefore, the melting behavior of iron tailings can be characterized by the melting behavior of silica. The time series images of silicon dioxide in high temperature molten pool during melting process are collected by CCD video camera system[3] (The experimental equipment is as follows).

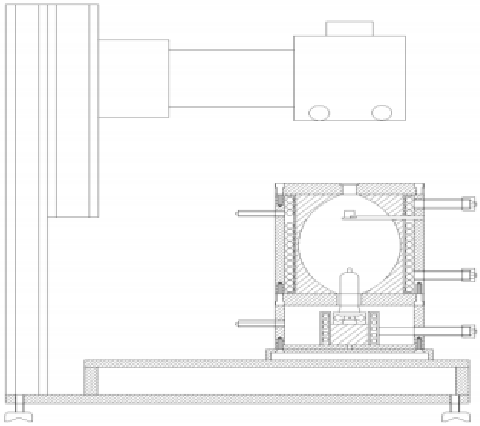


Figure 1 Drawing of Refitted CCD Equipment with Amplification Effect

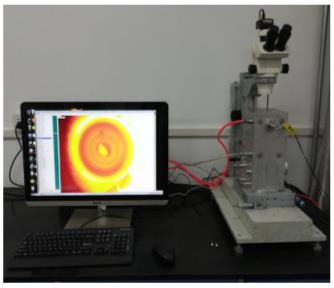


Figure 2 Diagram of Physical Equipment Object

2.1 Image processing

In order to obtain the region of silicon dioxide from 140 sequential images of silicon dioxide in the high temperature molten pool during melting, a new image was formed. In order to explore the dissolution behavior of SiO_2 in high temperature slag, the 140 images should be processed first.

2.1.1 Image enhancement

As shown in Figure 3, the picture provided for the topic. It can be seen that the picture is not clear and the area of silicon dioxide cannot be accurately obtained. Therefore, we must first enhance the image. Gray scale transformation enhancement is a simple and effective method for image enhancement in spatial domain. Gray scale transformation enhancement does not change the position of pixels in the original image, but only changes the gray scale values of pixel points, and is carried out point by point. In order to perform gray scale transformation, the histogram of the gray scale image must first be acquired. the histogram of fig. 3 is shown in fig.4.

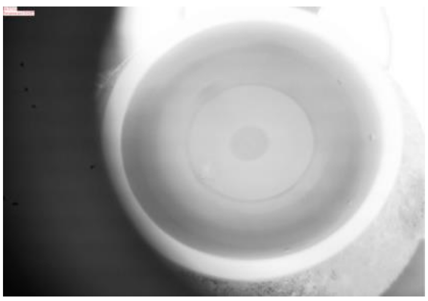


Figure 3 Original Picture

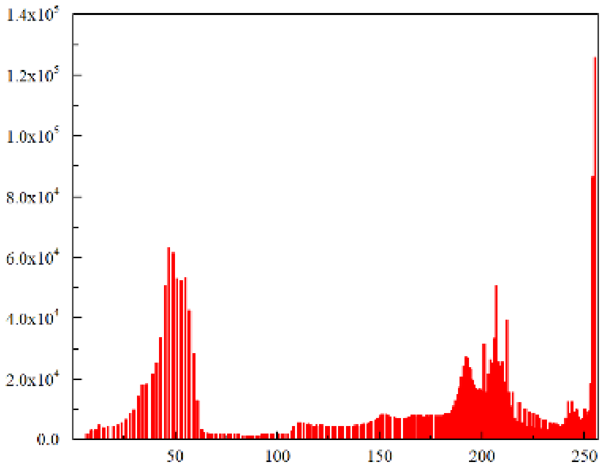
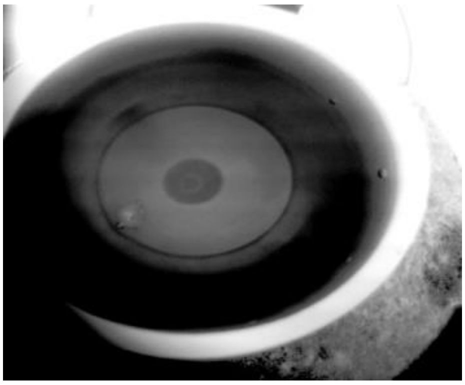


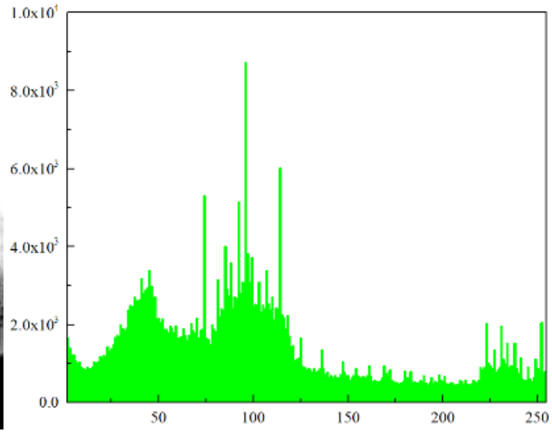
Figure 4 Histogram of Original Picture

As can be seen from fig. 4, the gray value of the image is mainly concentrated between 175 and 225, so the image is relatively blurred. We can make the image clearer by evenly distributing the gray value of the image between 0-255.At the same time, it is necessary to set the gray value less than 175 to be 0 and the gray value greater than 225 to be 255. If the gray value of the original image is set to X and the gray value of the enhanced image is set to Y, the following relationship is obtained:

$$\frac{x-175}{225-x}=\frac{y-0}{255-y} \tag{1}$$

Next, we will specifically adjust the gray scale range of the gray scale image. The enhanced image and its histogram are as follows:





(a) Optimized image (b) Histogram of Enhanced Image

Fig. 5 picture after image enhancement

2.1.2 Edge Detection Algorithm of Hierarchical Clustering

The hierarchical clustering algorithm uses the split hierarchical clustering algorithm in clustering analysis to cluster the pixel gradient in the 3×3 edge detection template, thus obtaining the edge of the image[5-7]. The method comprises the following steps of: firstly, obtaining absolute values of gray value differences between pixel center points in a pixel template and pixel points in all surrounding fields after median filtering, dividing the absolute values of the differences into a cluster, carrying out first splitting by comparing the gray value of the pixel points in the cluster with a given threshold value, dividing pixel points larger than the threshold value into a cluster, setting the pixel point value smaller than the threshold value to 0 and dividing the pixel point value into a cluster at the same time, and condensing and merging the pixel point gray values of the two clusters into a cluster, All pixel points in the condensed whole cluster are sorted in ascending order according to the gray values, the average value of the gray values of the third bit and the fourth bit is taken as an adaptive threshold, the average value of the gray values of all pixel points in the new cluster is compared with the adaptive threshold, split hierarchical clustering analysis is performed again, the judgment larger than the threshold is an edge, and the judgment smaller than the adaptive threshold is not an edge.Let the gray value of all pixel points in a 3×3 edge detection template after median filtering be P_k (k = 1, 2, ..., 9), and let the gray value of the template center point that needs to be judged as an edge point be P_5.The absolute value of the difference between the gray value of the Pixel center point in the pixel template and the pixel points in all surrounding areas is found to be $P_i = | P_k - P_5 |$, where i= 1,2, ..., 8,k = 1,2, ..., 9, and pi is divided into a cluster V.

The absolute value of the difference between the gray value of the Pixel center point in the pixel template and the pixel points in all surrounding areas is found to be $P_i = | P_k - P_5 |$, where i = 1,2, ..., 8,k = 1,2, ..., 9, and pi is divided into a cluster V.

The gray values of all pixel points in cluster a and cluster b are clustered into a new cluster C.

The average value P_a of gray values P_j (j = 1, 2,..., 8) of all pixel points in cluster C is calculated as follows:

$$p_a = \frac{\sum_{j=1}^{8} p_j}{8} \quad \text{(j=1,2...,8)} \quad (2)$$

Then the gray values of all pixels in cluster C are sorted in ascending order, and the new sorting is P_j (j = 1,2,..., 8).

The average value of the gray values of the pixels arranged in the 4th and 5th bits is taken as the adaptive threshold P_T, as shown in the following formula.

$$P_T = \frac{(P4` + P5`)}{2} \quad (3)$$

Finally, the elements P_j (j = 1, 2,..., 8) in cluster C are analyzed by split hierarchical clustering. If P_j is greater than the threshold P_T, it is determined as edge, otherwise, it is not.

2.1.3 Flow of Hierarchical Clustering Edge Detection Algorithm

According to the above analysis, 3×3 template is selected for edge detection. The algorithm flow of this paper is as follows:

Step 1: The collected real-time color image is converted into a gray image, and then median filtering is performed.

Step 2: Calculate the absolute value P_i (i = 1,2,..., 8) of the gray value difference between the pixel center point in the template and pixel points in all surrounding areas, and divide it into a cluster V.

Step 3: Compare P_i (I = 1, 2,..., 8) with a given threshold T to perform hierarchical clustering for the first split:

1) if $P_i \geq T$ (i = 1,2, ..., 8), it is classified as cluster A;

2) if $P_i \geq T$ (i = 1,2,..., 8), set P_i to 0 to cluster B.

Step 4: merge the elements in cluster A and cluster B to obtain a condensed hierarchical cluster C, wherein the elements P_j (j = 1, 2, ..., 8).

Step 5: Calculate the average value Pa of gray values P_j (j = 1, 2,..., 8) of all pixel points in cluster C.

Step 6: Sorting the elements in cluster C in ascending order to obtain a new sorting P_j (j = 1,2,..., 8).

2.1.4 Specific Image Processing Flow

After the image is enhanced, the previously mentioned hierarchical clustering is used to determine the boundary of SiO_2[8-10]. The algorithm is used to cluster the captured images, count the number of pixels in the iron tailings area, and analyze the specific physical process in combination with the number of pixels in the entire image and crucible outer diameter data. The specific treatment process is as follows:

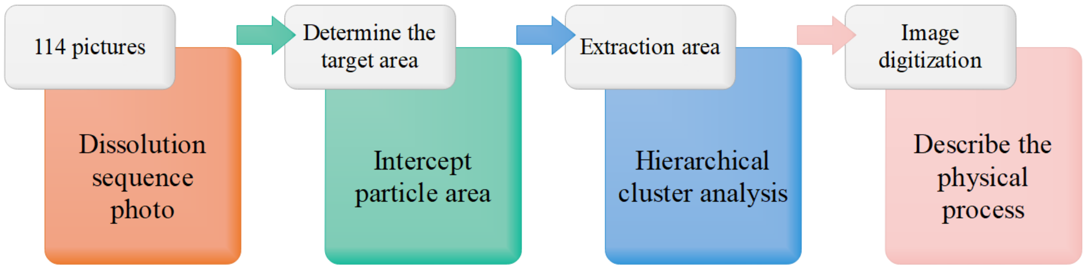


Fig. 6 Image processing flow

Part of the process of SiO_2 melting is shown in the following figure:

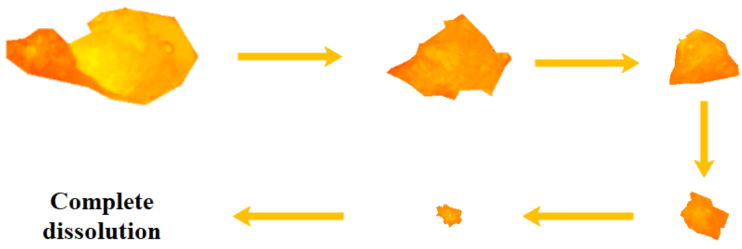


Fig. 7 The Whole Process of SiO2 Dissolution in Slag

3. Modeling

3.1 Trajectory of center of mass

The position is a time series. Here we set the position of the center of mass as($d(t),\theta(t)$), where $d(t)$ is the distance from the center of mass T to the center point P of the crucible, and $\theta(t)$ is the angle between the straight line P_T and the left half x axis. As shown in fig.8.

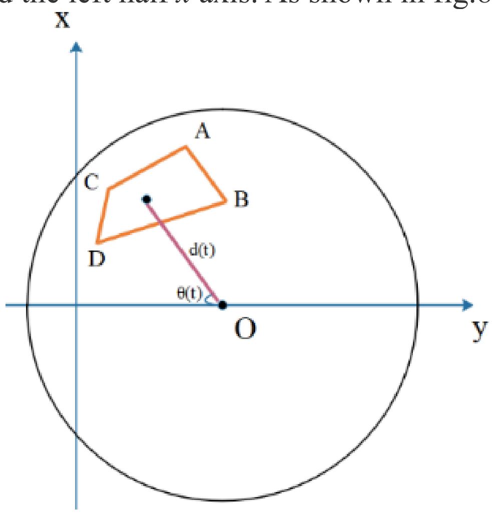


Fig. 8 Model demonstration

3.1.1 Model Building for d(x)

We measure the position of the SiO_2 centroid in the first 30 maps, and Make its scatter chart and line chart, as shown in figure.9 and figure.10.

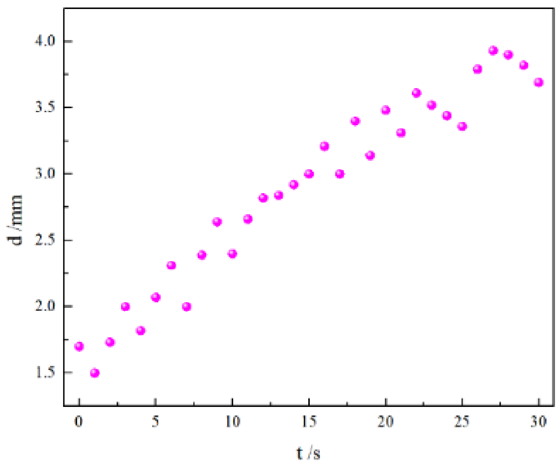


Fig. 9 Scatter plot of centroid distance

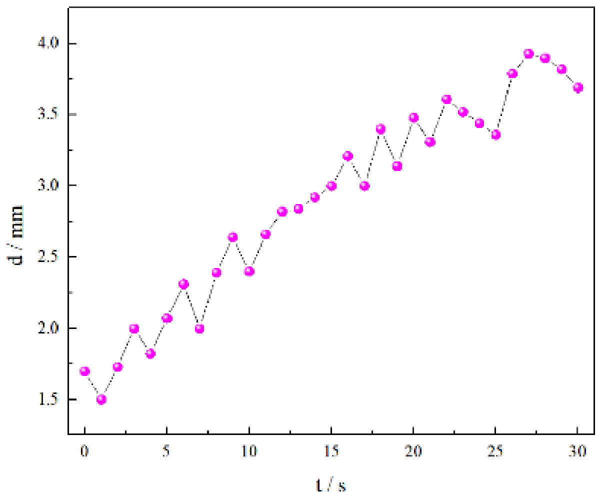


Fig. 10 Line chart of centroid distance

We found that the centroid position has periodicity and trend, which is the composite time series, so we established a time series decomposition model.

Separate seasonal components Divide each observation value by the corresponding seasonal index, and express it as *d(t)/S(t)=g(t)* with the formula.

The scatter chart and line chart are as follows:

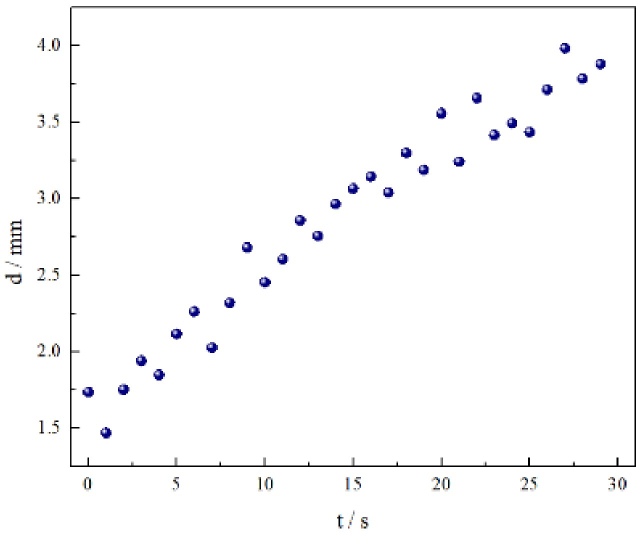


Fig. 11 Scatter plot of centroid distance after separation

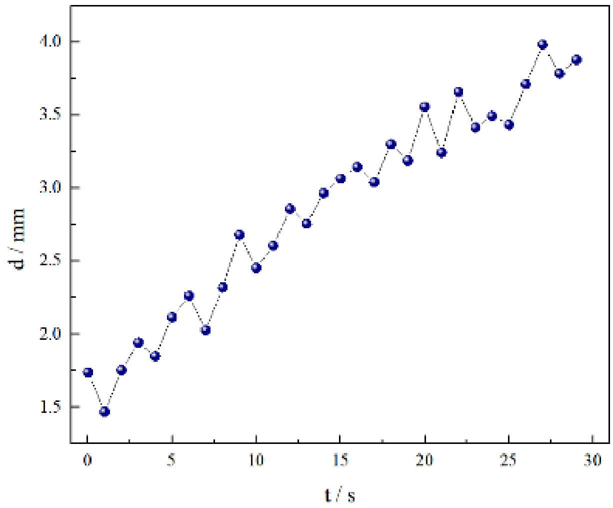


Fig. 12 Line chart of centroid distance after separation

Fig. 13 is obtained by fitting the separated centroid distance curve.

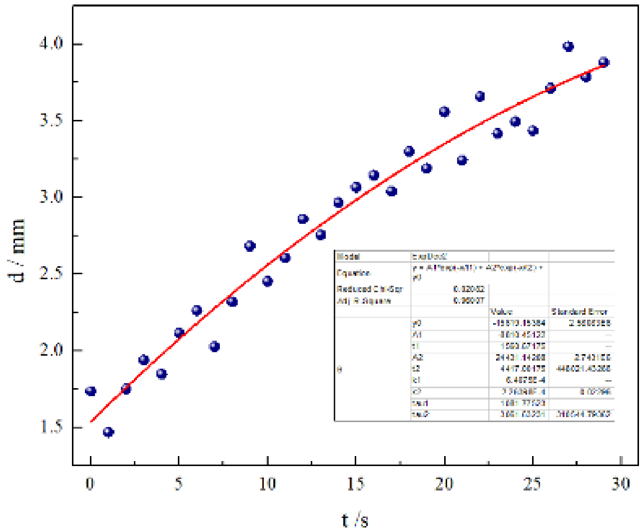


Fig. 13 Fitting Curve of Centroid Distance after Separation

Therefore, the function can be defined as:

$$d(t)=\begin{cases}0.9781\times(-0.0012t^2+0.1163t+1.4224)\langle t\in 5Z\rangle \\ 1.0207\times(-0.0012t^2+0.1163t+1.4224)\langle t\in 5Z+1\rangle \\ 0.98649\times(-0.0012t^2+0.1163t+1.4224)\langle t\in 5Z+2\rangle \\ 1.03023\times(-0.0012t^2+0.1163t+1.4224)\langle t\in 5Z+3\rangle \\ 0.98441\times(-0.0012t^2+0.1163t+1.4224)\langle t\in 5Z+4\rangle\end{cases} \quad (4)$$

For $\theta(t)$, since the early changes are extremely insignificant, we calculate it every five seconds and 19 times.Its scatter chart and line chart are as follows:

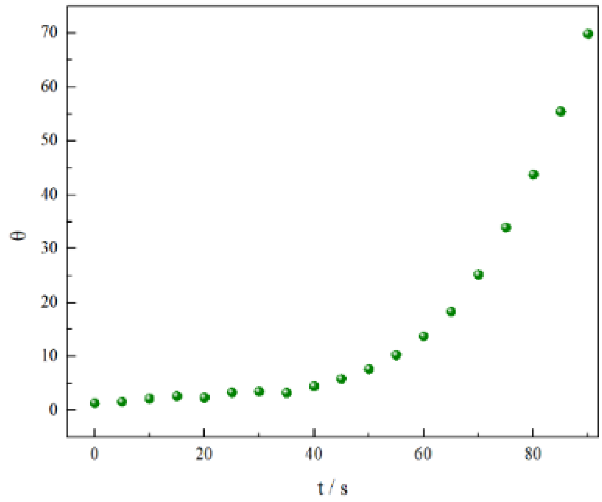


Fig. 14 Centroid angle scatter plot

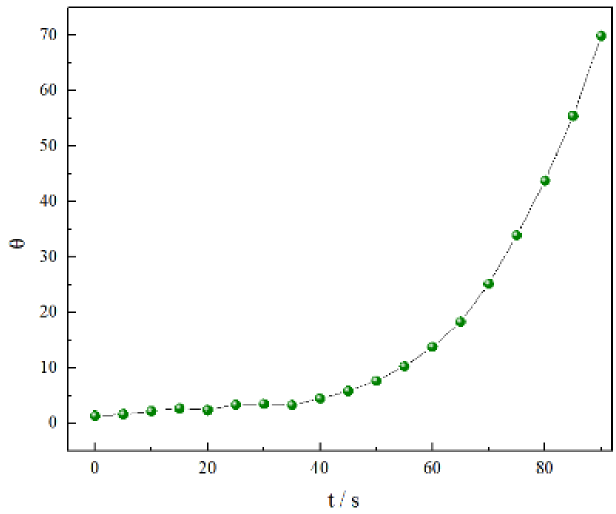


Fig. 15 Line chart of centroid angle

We found that the graph has trend and only slight interference, and the trend approximates an exponential curve. Let the trend equation of exponential curve be $YT_t`=b_0b_1^t$ , where $b_0,b_1$ is undetermined coefficient. Obviously $b_0>1$, there is $lgYT_t`=lgb_0+lgtb_1^t$ for logarithms on both sides of the equation Here we use the least square method to solve b_0,b_1 with the following equation.

$$\begin{cases}\sum \lg Y = 19\lg b_0 + \lg b_1 \sum t \\ \sum t \lg Y = \lg b_0 \sum t + \lg b_1 \sum t^2\end{cases} \quad (5)$$

The solutions are b_0=1.0621, b_1=0.0442. So there is $\theta(t)=Y=1.0621e^{0.0442t}$.

To sum up, for any time t, the position of the center of mass is$(d(t),1.0621e^{0.0442t})$, and its trajectory curve is shown in the figure.

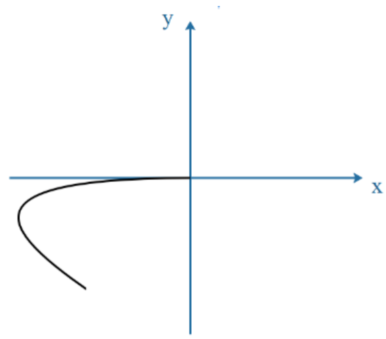


Fig. 16 The change curve of (d(t),1.0621e0.0442t)

3.2 Morphology and area of iron tailings in melting process

Since the given picture is extremely irregular and very troublesome in calculating the diameter, we define the diameter as follows: Let *E* be a closed interval (considering only the two-dimensional case), *E* be a closed interval formed by the area enclosed by the quadrilateral *BCDE* plus the boundary, and *a* be the center of a circle containing the quadrilateral *BCDE*. it is defined as follows:

$$\begin{aligned} P &= \inf\{d(a, e), e \in E\} \\ Q &= \sup\{d(a,e), e \in E\} \end{aligned} \quad (6)$$

Definition diameter: *l=d(P,Q)* is shown in Figure 17:

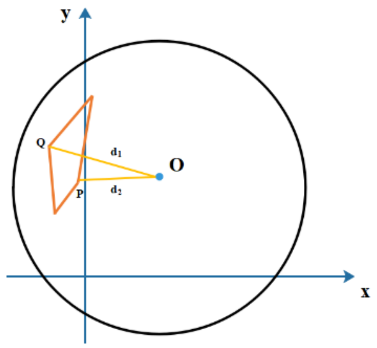


Fig.17 Model demonstration

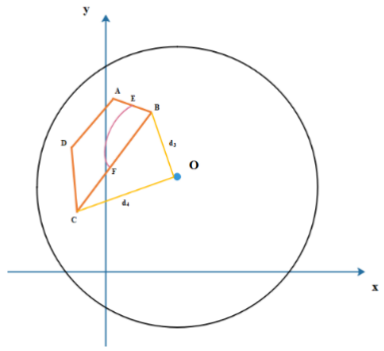


Fig.18 Model demonstration

Obviously, for a fixed irregular two-dimensional figure and the closed interval formed by the boundary, when it is gradually reduced, the shape of the image will change, and it is gradually reduced. At last, the graph tends to be a curve, which is *FG* with the same distance from the center of the circle. Obviously, the measure is 0, so the area is 0. So the diameter we defined is meaningful. As shown in Figure 18. As the diameter of SiO_2 decreases with time, we know that the diameter is a function of time, and we record it as *l=f(t),* Therefore, for the calculation *l=d (a, b)-d (a, d)* of the diameter of any irregular figure, as shown in Fig 19;

We select the first 30 groups of pictures to calculate the diameter data. In order to reduce the error, we measure three times and take the average value as our diameter.

Analyze the data with excel as follows:

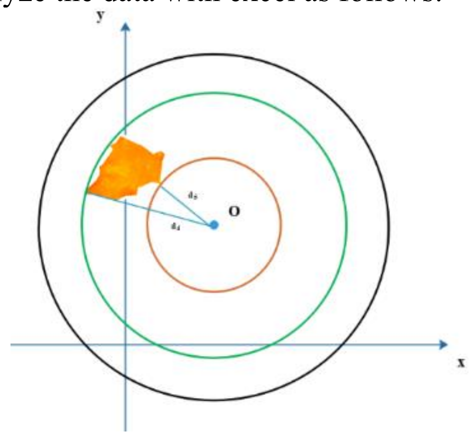


Fig.19 Model demonstration

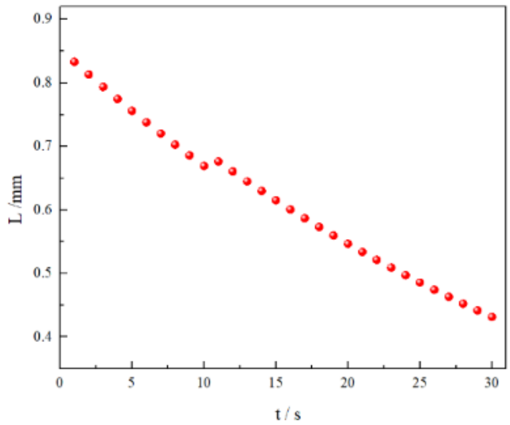


Fig.20 Scatter plot of generalized diameter

It is approximate to the form of an exponential function, so we assume that the function form is

$$l = f(t) = a \times e^{bt} \quad (7)$$

The logarithm of two sides is: *lnf(t)=bt+lna* Processing the data to obtain:

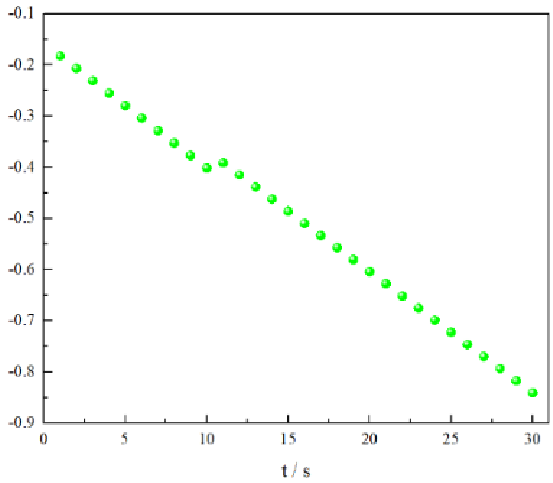


Fig.21 Scatter plot of generalized diameter after taking logarithm

The result of fitting function by least square method is y=-0.223x-0.1621. So we can get the function:

$$l = f(t) = 0.8503 \times e^{-0.022t} \quad (8)$$

3.3 Quantitative characterization of melting rate at different times

Take any point q from the origin o as l_0 and take the infinitesimal δl. We have $\delta l = V\delta t$. Since the diameter l has a function $l=f(t)=0.8503\times e^{-0.022t}$ with time, and the melting rate V is only related to mass, and mass is a function of time, we know that the rate V is a function of time. Therefore, the integral is taken simultaneously on both sides of equation $\delta l = V\delta t$, and the process is as follows:

Select dl at l_0. Thus $dl=V(t_0)\ dt$dt can be obtained. The integration of l from 0 to l_0 is as follows:

$$\int_0^{l_0} dl = \int_0^n V(l)dt \quad (9)$$

There are:

$$l_0 = \int_0^n V(l)dt \quad (10)$$

Due to:$l=f(t)=V(l)=V(t)$

There are:

$$l_0 = \int_0^n V(t)dt \quad (11)$$

Due to:

$$\int_0^l dl = \int_0^t V(l)\mathrm{d}t \quad (12)$$

l can be expressed as:

$$l = \int_0^t V(t)dt \quad (13)$$

Find the derivative on both sides of $l=f(t), f`(t)=V(t)$

So we can get its equation:

$$\mathrm{V(t)} = 0.0187\mathrm{e}^{-0.022\mathrm{t}} \quad (14)$$

The velocity variation curve can be given as shown in the figure.22

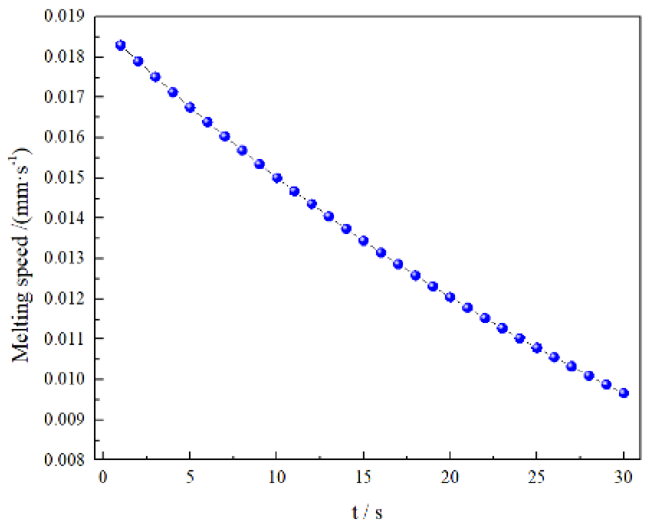


Fig.22 Dissolution rate variation curve

4. Conclusion

In this paper, 140 sequential images of silicon dioxide in high temperature molten pool during the melting process are taken as the research object. The piecewise function and the angle exponential function of the distance from the center of mass to the center of the crucible are proposed, which the movement track of dissolved mass center of iron tailings is measured. The morphology and area of iron tailings in the melting process is measured by generalized diameter method, and the melting rate at different times is quantitatively characterized by micro element method. The research realizes the online and real-time measurement of physical parameters in the melting process of high-temperature blast furnace iron tailings which promotes the direct fiber-forming process of blast furnace slag to a certain extent.

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