Extraction of Blast Furnace Burden Line Based on Radar Spectrum Restructured by Entropy Weight

Qiudong Shi¹, Fenxian Ye¹, Wenzhi Dang¹, Yanan He¹, Qingwen Hou¹* and Xianzhong Chen¹

¹School of Automation and Electrical Engineering, University of Science and Technology Beijing, Beijing, 100083, China.
*Corresponding author’s e-mail: houqw@ustb.edu.cn

Abstract. Hostile environment inside blast furnace (BF) and nonuniform fluidization characteristics of burden surface bring challenges to the extraction of burden line, which is an important factor affecting the smelting efficiency. In this study, based on the imaging principle of Synthetic Aperture Radar (SAR), a mechanical swing radar was designed to capture the high-density radar echo signals. By analyzing the characteristics of radar spectrum, the entropy weight method was used to complete the coordinate transformation from the nonuniform coordinate point cloud map to the grayscale image in real space to visualize the smelting states. Then, the burden surface features were enhanced by gamma correction, and the adaptive threshold segmentation was used to extract the surface transitional belt in the image. Finally, the burden line points were extracted by the energy centrobaric correction method to fit the burden line. Compared with traditional algorithm, experiments on industrial data indicate its feasibility and effectiveness.

1. Introduction

Accurately capturing the shape and position information of the blast furnace (BF) surface is helpful to improve gas flow distribution and adjust burden distribution matrix, which is essential in the metallurgy industry [1]. The blast furnace is a “black box” equipment with huge energy consumption, the harsh environment of high-temperature, high-pressure, and high-dust inside the BF, and the inhomogeneous fluidization characteristics of burden surface make it difficult to monitor the burden surface, which is one of the pain points in the steel industry. Shi et al. used an infrared imager installed atop a furnace to identify the distribution of the central BF gas flow [2]. Chen et al. designed a parallel low-light-loss backlight high-temperature industrial endoscope to obtain images of the full burden surface of a BF, but its fixed viewing angle made the surface image lack depth information [3]. He et al. used phased array radar data to estimate the surface shape of the burden surface by a weighted least squares estimation and B-spline interpolation [4]. Chen et al. proposed a frequency-modulated continuous wave (FMCW) industrial high-temperature radar based on the point-by-point measurement method, which realized continuous monitoring of the burden surface height on the industrial site [5]. Compared with infrared imager and endoscope detection, FMCW radar has strong penetrability and is not affected by the high temperature dust, smoke, and water vapor inside the BF [6], a new generation of mechanical swing radar (MSR) based on the principle of SAR imaging is of increasing interest to international academic and industrial circles.

Because of the hostile environment inside the BF, the microwave near-field antenna corrosion and adhesion, and the Rayleigh clutter of the burden surface itself, radar echo signals often show unstable
signal-to-noise ratio (SNR) characteristics. Zhao et al. acquired the instantaneous frequency characteristics of signals based on an empirical mode decomposition and the Hilbert-Huang transform (HHT), this approach was combined with the C4.5 decision tree algorithm and prior knowledge to reconstruct the signal, and it improved the SNR of the echo signal [7]. Hou et al. proposed the distance inversion method of CZT refinement and frequency band energy weighting in key areas with the aid of a priori information in response to the problem of low SNR radar signal range broadband ambiguity [8]. The traditional algorithm assumes that the maximum energy point of the radar echo signal after FFT transformation is used as the burden surface position, but the nonimaging method using peak searching ignores the large amount of effective information contained in the echo spectrogram and cannot accurately reflect the relationship between the shape and position of the gas-solid medium inside the BF. Tian et al. proposed a radar burden surface detection B-model, in which the matrix composed of the detection results of the radial shape of the burden surface within a scanning period is represented by a composite image and adopted an image segmentation algorithm based on a prior curve to obtain more reasonable segmentation results in the noncharging period [9].

To extract burden line information exactly, the frequency-modulated continuous wave (FMCW) radar, which swings in the radial direction of the BF, is designed to capture the echo signal of the burden surface by single scanning. Through simulating the SAR imaging technology, the radar swing angle is introduced to construct the point cloud map. Then, the coordinate transformation from the point cloud map matrix to the burden surface grayscale image matrix in the actual space is completed by the entropy weight method. After this step, gamma correction is used to enhance the burden surface features, and the surface transitional belt is extracted by the adaptive threshold segmentation. Finally, the energy center of gravity principle is used to extract energy points of the burden surface to fit the burden line. The performance of the proposed method is verified by the measured data of the steel mill, and the results of the burden line are compared with other algorithms.

2. Background
The mechanical swing radar (MSR) is installed on the inclined furnace wall above the furnace throat, which can effectively reduce the interference of rotating chute. The MSR based on the FMCW ranging principle works in the band of 26GHz, and the radar signal acquired is in the standard 1024-point data format. Figure 1 shows the radar scanning diagram in the BF. The radar antenna is driven by the servo system and swings from the furnace wall to the furnace center at a uniform angular velocity along the radial direction of the burden surface. The echo signal of half of the burden surface is acquired by single scanning.

![Figure 1. Schematic diagram of the radar scanning.](image)

The O-XY coordinate system in the figure is the BF longitudinal profile coordinate system, in which the X-axis coincides with the zero feed line, the Y-axis is the central axis of the profile, \( R \) is the distance from the radar to the axis of the BF, and \( H \) is the distance between the radar and the zero feed line, \( R \) is the BF radius. The coordinates \((x_i, y_i)\) of measuring point \( S_i \) is calculated as
where $L_i$ is the direct distance from the radar to $S_i$, and $\theta_i$ is the angle between the radar antenna direction of $S_i$ and the vertical direction.

According to the acquisition time, a single scan of the radar can obtain a set of echo signals of burden surface points. The time domain signal is filtered to remove the DC component and operated with the Fast Fourier Transform (FFT) into the frequency domain. Because the burden surface distance is in a limited range, the first 120 spectrum numbers represent all valid information and form a spectrum matrix $A_{120 \times N}$, $X_i$ is denoted as spectrum data of the sample points.

\[
A = [X_1, X_2, \cdots, X_N]
\]

\[
X_i = [X_{ij}, X_{ij+1}, \cdots, X_{ij+120}], i = 1, \cdots, 120
\]

The matrix can be projected into a standard 64-order image, defined as a two-dimensional (2D) spectrogram of the radial echo signals of the burden surface, as shown in (a) and (c) of figure 2. The burden surface is a fuzzy layer fluctuating within a certain range, which is caused by its unsteady rough fluidization interface characteristics and splashing particles. (c) and (d) of figure 2 is the energy intensity distribution of the peak ridge in the three-dimensional (3D) space, and the amplitude can be used as an important feature of the sharpening of the peak ridge and the identification of the burden surface. However, due to the interference of dust and airflow in the BF, the details of the energy peak ridge of the transition zone are not clear, showing an intermittent and unsteady state.

![Figure 2. Radar signal characteristic spectrum.](image)

The MSR imaging is similar to the SAR imaging mechanism and mainly focuses on range resolution. The polar angle of the furnace wall is $\alpha_1$, the polar angle of the furnace center is $\alpha_2$, $\beta$ is the installation angle of the radar, the radar swing angle $\theta$ can be expressed as

\[
\begin{aligned}
\alpha_i &= \arctan((R - R_i)/H) + \beta \\
\alpha_2 &= -\arctan (R/H) + \beta \\
\theta &= |\alpha_i - \alpha_2|
\end{aligned}
\]

The corresponding angle $\theta_k$ of the discrete spectrum of the kth echo in the spectrum matrix $A_{120 \times N}$ is obtained by equation (4).

\[
\theta_k = \alpha_i - \frac{k}{N} \theta, k = 1, \cdots, N
\]

Distance conversion is performed on the spectrum number of the spectrum matrix $A_{120 \times N}$.

\[
L_m = K \times m_d
\]

where $K$ is the radar ranging coefficient, $K = 0.0915$ [10], $m$ is the echo spectrum number, and $m = 1, \cdots, 120$. 

3
The coordinates \((x_{m,k}, y_{m,k})\) of each measuring point can be obtained by equation (1). Then, the nonuniform coordinate matrix \(I_{m,k}(x_{m,k}, y_{m,k})\) is obtained, where \((x_{m,k}, y_{m,k})\) is the coordinate matrix and \(I_{m,k}\) is the amplitude matrix, and its value has a one-to-one correspondence with matrix \(A\). Figure 3 shows the sector point cloud distribution map of the scattered energy of materials in the BF.

Figure 3. Sector point cloud distribution map.

3. Burden surface grayscale image construction and burden line extraction

This section is aiming at extracting the surface transitional belt and burden line. Coordinate transformation and matrix compensation from the point cloud map to the burden surface grayscale image are completed by the entropy weight method and gamma correction. After burden surface region segmentation, the burden line is extracted by the energy centrobaric correction method.

3.1. Grayscale image construction of the burden surface

Firstly, the amplitude matrix \(I_{m,k}\) is converted into a grayscale matrix \(U_{m,k}\) of 0-255. Figure 4(a) shows the positional relationship between the nonuniform coordinates and image pixels. The black points represent the grayscale at a corresponding angle at a certain frequency in the point cloud map under the polar coordinate system, \((x_{m,k}, y_{m,k})\) is the position of the black point in the Cartesian coordinate system, and \(U_{m,k}\) is the grayscale value of the point. The white points represent the interpolation points in the standard image. This study proposed a resampling interpolation method based on the entropy weight to convert the nonuniform coordinate pixels to uniform coordinate pixels. The entropy weight method determines the weight of the pixel value of the original sampling point according to the selected index variability, and then the pixel value of the point to be interpolated is determined by weighting.

The interpolation schematic is shown in figure 4(b). For an interpolation point \(P_0(x_0, y_0)\) in the Cartesian coordinate system, determine the number \(N\) of sampling points in the neighborhood. Index one is the pixel value \(u_i\) of sampling point \(P_i(x_i, y_i)\) in the neighborhood, and index two is the Euclidean distance between the sampling point and the interpolation point. The proposed interpolation algorithm is described as follows:
The pixel value $u_i$ of the sampling point $P_i$ in the neighborhood is standardized to ensure the comparability between the features that characterize the different indicators.

$$u_i' = \frac{u_i - u_{imin}}{u_{imax} - u_{imin}}$$  \hspace{1cm} (6)

where $u_{imin}$ and $u_{imax}$ are the minimum and maximum pixel values of the sampling points.

The entropy values $e_j$ of index one and index two are calculated by equations (7) and (8).

$$p_{ji} = \frac{u_i'}{\sum_{i=1}^{N} u_i'}$$  \hspace{1cm} (7)

$$e_j = -\frac{\sum_{i=1}^{N} p_{ji} \ln p_{ji}}{\ln N}$$  \hspace{1cm} (8)

where $p_{ji}$ is the proportion of the index value of the $i$th sampling point under the $j$th index.

The index weight $w_j$ is defined as

$$w_j = \frac{1 - e_j}{\sum_{j=1}^{2} (1 - e_j)}$$  \hspace{1cm} (9)

In this case, the weight $k_i$ of the sampling point can be expressed as

$$k_i = \sum_{j=1}^{2} w_j p_{ji}$$  \hspace{1cm} (10)

The pixel value $v_0$ of the interpolation point can be obtained by equation (11).

$$v_0 = \frac{\sum_{i=1}^{N} u_i k_i}{\sum_{i=1}^{N} k_i}$$  \hspace{1cm} (11)

After the interpolation point matrix is symmetrical, the grayscale matrix $V$ of the burden surface can be obtained. The real scanning space of the radar is 4.8 meters in radius and 12.8 meters in depth. The ratio of the reconstructed grayscale image to the size of the real space is 1:50, and the image resolution is $640 \times 480$.

3.2. Gamma-based burden surface features enhancement

The harsh environment in the BF results in various interference noises in the image. Nonlinear median filtering can effectively suppress some random interference pixels in the grayscale image and can maintain the sharpness of the edge of the burden surface region. Image enhancement in spatial domain can adjust the contrast between light and dark of grayscale image, and enhance the grayscale value of signal in the burden surface region. The length of the median filter window is $2 * n + 1$, where $n$ is a positive integer. The set of all pixels in the window is

$$M_y = \{y(i+s, j+t)|s,t \in [-n,n]\}$$  \hspace{1cm} (12)

All $(2 * n + 1)^2$ pixels in the set $M_y$ are sorted in a certain order according to the grayscale value.

$$Y: y_1 \leq y_2 \leq \cdots \leq y_{(2n+1)^2}$$  \hspace{1cm} (13)

The pixel value $y_{(i,j)}$ of a point in the image can be replaced by the median value in the neighborhood.

$$y_{(i,j)}^{new} = Med(Y) = Y\left(\frac{(2n+1)^2+1}{2}\right)$$  \hspace{1cm} (14)
The size of the window template can be adjusted according to actual needs. After filtering, the grayscale histogram distribution of the surface image is counted by equation (15).

\[ P(\text{num}_i) = \frac{n_i}{N} \quad (i = 0,1,2,\cdots,M - 1) \]  

where \( n_i \) is the number of pixels in the \( i \)th grayscale level, \( M \) is the number of grayscale levels, and \( N \) is the total number of pixels in the image.

Gamma transformation can realize the non-linear stretching of the image, and redistribute the image pixel value, thereby improving the image brightness imbalance. The gamma algorithm can be described as

\[ G = cr^\gamma, \quad r \in [0,1] \]  

where \( r \) is the input grayscale value, \( c \) is the constant, and \( \gamma \) is the gamma correction coefficient.

According to the grayscale histogram, the grayscale interval \([m_1,m_2]\) is select to be transformed. Suppose \( x \) is located in the interval \([m_1,m_2]\). Firstly, the grayscale value in the interval is normalized.

\[ x' = \frac{x - m_1}{m_2 - m_1} \]  

The gamma transform of the grayscale value \( x' \) can be expressed as

\[ x' = x'^\gamma = \left(\frac{x - m_1}{m_2 - m_1}\right)^\gamma \]  

Then, the grayscale value \( x' \) is mapped to the interval 0–255.

\[ y = 255 * x' = 255 * \left(\frac{x - m_1}{m_2 - m_1}\right)^\gamma \]  

Finally, for the grayscale value \( x \) of each pixel in the original surface image, the gamma transformation is performed as follows:

\[ y = \begin{cases} 
0 & x < m_1 \\
255 * \left(\frac{x - m_1}{m_2 - m_1}\right)^\gamma & m_1 \leq x \leq m_2 \\
255 & x > m_2 
\end{cases} \]  

The overall mapping process from the sector point cloud distribution map to the grayscale image is shown in figure 5.

Figure 5. Image conversion process.

3.3. Burden surface region segmentation and burden line extraction

After the image is enhanced, the burden surface target is in obvious contrast with the background, and the grayscale level difference is large. The target region can be extracted by the adaptive block-based maximum interclass variance method. Suppose \( f_{(x,y)} \) is the grayscale value of a certain point in the burden surface image \( I_{H \times W} \), and the grayscale range is \([0,L-1]\). The probability \( p(m) \) of the grayscale value in the image is expressed as

\[ p(m) = \sum_{f_{(x,y)} = m} \frac{1}{H \times W} \]  

(21)
If there is a threshold \( t \) that can distinguish between the target and the background, the probability of the target and the background image \( W_1 \) and \( W_2 \) is described as

\[
w_1(t) = \sum_i p(i) \quad \text{and} \quad w_2(t) = \sum_i p(i) \tag{22}\]

The mean \( u_1 \) and \( u_2 \) of the target and the background are calculated as

\[
u_1(t) = \frac{\sum_i i \cdot p(i)}{w_1(t)} \quad \text{and} \quad \nu_2(t) = \frac{\sum_i i \cdot p(i)}{w_2(t)} \tag{23}\]

The average grayscale value \( u \) of the image is expressed as

\[
u(t) = w_1(t) \cdot \nu_1(t) + w_2(t) \cdot \nu_2(t) \tag{24}\]

In this case, the interclass variance \( \sigma^2 \) between the target and the background can be expressed as

\[
\sigma^2(t) = w_1(t)(u_1(t) - u(t))^2 + w_2(t)(u_2(t) - u(t))^2 \tag{25}\]

Finally, the optimal threshold \( t' \) that makes \( \sigma^2 \) obtain the maximum value can be expressed as

\[
t' = \arg \max_{0 \leq t \leq L} \sigma^2(t) \tag{26}\]

The image \( I_{HWI} \) is divided into \( r \times r \) blocks, and the average interclass grayscale \( \varepsilon_{(m,n)} \) of each block can be obtained by equation (27).

\[
\varepsilon_{(m,n)} = |u_1(t) - u_2(t)|, \quad m, n \subset [1, r] \tag{27}\]

When a block only contains the background, the \( \varepsilon_{(m,n)} \) will be small, so we can set a threshold to process the block containing the target to obtain the surface region.

The energy centrobaric correction method [11] is suitable for spectrum correction, and can get the normalized frequency value according to the energy distribution of the spectrum. We can use it to extract the burden line points in the surface transition belt. The pixel value of the grayscale image of the burden surface can be characterized as the energy value. Assuming that the energy value of the highest spectral line in the spectrum is \( e(l) \), the energy sum of \( D \) sub-peak spectral lines in its neighborhood can be calculated as

\[
E = \sum_{i=0}^{D} e(l + i) \tag{28}\]

Then, the normalized frequency value \( \lambda \) can be expressed as

\[
\lambda = E \cdot (\sum_{i=0}^{D} e(l + i))^{-1} \tag{29}\]

After calculating the main energy points in each column of image matrix \( I_{HWI} \), the burden point matrix \( K_{BFO} \) can be obtained, and Gaussian fitting is carried out to extract a smooth fluctuating burden line.

4. Industrial data experiments

4.1. Radar imaging

In order to verify the reliability of the BF radar imaging system, a real burden surface model is built in the NG steel plant laboratory. Figure 6 shows the schematic diagram of the model. According to the model parameters of figure 6, a cold state burden surface model is built with iron ore and coke, as shown in figure 7.
The radar scanning image is shown in figure 8. The shape and parameters of the surface transition belt in the image are consistent with the real stacking surface. After many experiments, the position of the upper and lower boundaries of the burden surface in the image overlaps with that of the real model interface, and the marking error is less than 3%, effectively verifying the reliability of the burden surface measurement by radar.

![Figure 6. Schematic diagram of the model.](image1)

![Figure 8. Radar scanning image.](image2)

![Figure 7. Model of actual burden surface. (a) is the top view, (b) is the right view.](image3)

**4.2. Burden line extraction**

This study utilizes the experimental data from the WH steel plant No.7 BF to construct the grayscale images (850 in total). Figure 9 shows the burden surface images under different complex background noises.

![Figure 9. Burden surface images. (a) no noise, (b) fixed ring noise, (c) strong central airflow, (d) strong background noise.](image4)

![Figure 10. Results of burden line extraction.](image5)

The result of the burden line extracted on the burden surface transition belt is shown in figure 10. The traditional method uses pass-band FIR filters and peak searching to extract the burden line point, and then the burden line is fitted by the cubic spline smooth. According to prior knowledge, the true expected burden lines are marked. The compared results of the traditional method and the proposed method are shown in figure 11. Meanwhile, taking mean absolute error (MAE) and root mean square error (RMSE) as evaluation indicators, the comparison results of two methods on the grayscale images (850 in total) are calculated as shown in table 1. Formally, MAE is defined as
The RMSE is defined as

$$RMSE(y, y^*) = \left( \frac{1}{N} \sum_{i=N} \left| y_i - y_i^* \right|^2 \right)^{1/2}$$  \hspace{1cm} (31)$$

**Figure 11. Comparison results of the burden line.**

**Table 1. Comparison of MAE and RMSE on the image dataset.**

| Method           | MAE   | RMSE  |
|------------------|-------|-------|
| Traditional method | 0.1682 | 0.2433 |
| Proposed method  | 0.0587 | 0.0631 |

The results of the traditional method can basically reflect the trend of the burden surface when the jamming noise inside the BF is small, but there are many gaps with the expected burden line, such as at the burden surface edge. In the case of bad furnace conditions, such as strong central airflow and high noise, the burden line extracted by the proposed method is more consistent with the expectation, and it can avoid local outliers and overcome the deficiency of anti-interference ability of the traditional signal processing method. As shown in Table 1, the proposed method has achieved a MAE of 0.0587 and RMSE of 0.0631, thereby outperforming the traditional method and achieving high accuracy and robustness.

5. **Conclusion**

This study proposed a burden line extraction method for complex industrial high-temperature images. Based on the SAR imaging principle, the radar characteristic spectrum is constructed. By leveraging the entropy weight method, the BF radar spectrum is converted to burden surface grayscale image, and the true changes in burden surface morphology under a closed environment are visualized. Experiments on industrial data demonstrate that the burden line extraction after image segmentation can accurately reflect the change of the burden surface in the blast furnace, which contributes to outlining the burden layer, and optimizing burden distribution matrix. Considering that the life of industrial radar antenna is limited, the burden surface information will be blurred and even be submerged by the strong noise when the radar is at the end of its service life. The current burden surface information extraction algorithm is not perfect and has some limitations, so a new intelligent burden surface image processing algorithm is the focus of future research opportunity.

**Acknowledgments**

This research was partially supported by the National Natural Science Foundation of China (NSFC Grant No. 61473034 and No. 61671054), and the Beijing Municipal Natural Science Foundation (Grant No. 4182038).
References

[1] Zhou, P., Lv, Y., Wang, H., Chai, T. (2017) Data-driven robust RVFLNs modeling of a blast furnace iron-making process using cauchy distribution weighted m-estimation. IEEE Trans. Ind. Electron., 64: 7141-7151.

[2] Shi, Y., Wen, Y.B., Zhao, G.S., Yu, T. (2016) Recognition of blast furnace gas flow center distribution based on infrared image processing. J. Iron. Steel Res. Int., 3: 203-209.

[3] Chen, Z., Jiang, Z., Gui, W., Yang, C. (2016) A novel device for optical imaging of blast furnace burden surface: parallel low-light-loss backlight high-temperature industrial endoscope. IEEE Sens. J., 16: 6703-6717.

[4] He, Z., Yin, Y., Zhang, S. (2016) Burden surface fitting and the design of simulation platform for the blast furnace burden distribution. In: 2015 IEEE International Conference on Communication Problem-Solving (ICCP). Guilin, pp. 72-77.

[5] Chen, X., Liu, F., Hou, Q., Lu, Y. (2009) Industrial high-temperature radar and imaging technology in blast furnace burden distribution monitoring process. In: 2009 9th International Conference on Electronic Measurement & Instruments. Beijing. pp. 1599-1603.

[6] Znakl, D., et al. (2015) BLASTDAR-a large radar sensor array system for blast furnace burden surface imaging. IEEE Sens. J., 15: 5893-5909.

[7] Zhao, X., He, S., Chen, X., Hou, Q. (2016) Machine learning algorithm of blast furnace radar signal in strong interference environment. Control Theor. Appl., 33: 1667-1673.

[8] Hou, Q., Xu, Z., Lu, Y. (2015) Low SNR FMCW Signal Processing with Prior Information. Chin. J. Eng., 37: 366-372.

[9] Tian, J., Tanaka, A., Meng, Y., Hou, Q., Chen, X. (2019) Tracking the burden surface radial profile of a blast furnace by a B-model mechanical swing system. ISIJ Int., 60: 1667-1673.

[10] Hou, Q., Chen, X., Wang, X., Yin, Y., Li, X. (2010) Improved FMCW signal weighted compensated correction phase difference method. Chin. J. Sci. Instrum., 31: 721-726.

[11] Ding, K., Zheng, C., Yang, Z. (2010) Precision analysis and improvement of frequency correction by the center of gravity method of discrete spectrum energy. Chin. J. Mech. Eng., 46: 43-48.