An intelligent recognition and quantification system for photomicrographs of iron ore sinter is useful and convenient; however, it is impossible to develop a successful intelligent system without adequate and accurate texture features of mineralogical phases. The gray-level co-occurrence matrix (GLCM) has been proved as an effective method for extracting the texture features in other fields, therefore, this work examines texture features for the main mineralogical phases, such as magnetite and calcium ferrite, based on GLCM. These features include contrast, energy, entropy, and inverse difference moment. Specifically, this study addresses the effect on these features of several parameters, including the gray levels, the size of the image window, and the distance between the co-occurrences, and the offset angle. When the gray levels equal 125, the size of image window equals 100, and the distance of the co-occurrence equals 15, the average values of the four offset angles indicated that the features of each phase were relatively constant. Space distance characterizes the differences between a known image and an image to be analyzed; it determines the texture pattern of the image and is calculated using the Canberra space distance equation. Further calculation validates the results, indicating that intelligent recognition and quantification systems can be developed based on this method.

KEY WORDS: gray level co-occurrence matrix; image recognition; texture feature; mineralogical phase; iron ore sinter.

1. Introduction

Improvements in blast furnace operation depend on the quality of its burden, mainly the coke and iron ore sinter. Sinter quality is determined by a complex combination of operational parameters, including preparation of the sintering mix, ignition of the mixture, strand speed, bed depth, gas flow rate, and so on. Throughout the development of iron ore sintering, mineralogical analysis has been important as a means to understand the properties of sinter and the effects of each step in the sintering process.

For some time, research interest in the iron ore sintering industry was lacking. Recently, however, the world’s resources for iron ore have become scarce, and many low grade ores must now be used in sintering mixtures. The use of such ores directly affects the operation of sintering and the physical and chemical properties of iron ore sinters. To improve the agglomeration technology, guarantee the quality of iron ore sinter, and minimize the effects on hot metal production, accurate quantification of mineralogical parameters is necessary. Development of precise parameters will also help researchers understand the sintering mechanism.

Digital image processing was first developed in the 1920s, and it has been used widely ever since, especially since the invention of third-generation computers. Image processing techniques can be adapted for use in many fields. In 1977, Jeulin introduced a method to analyze the quantitative morphology of iron ore sinter using morphological operations such as image erosion, image dilation, and border detection. Use of this technique has matured significantly to permit quantification of size and spatial distributions of components and programming of the morphological operations of the texture analyzer so that it can take measurements on detected images. These morphological operations also permit signal enhancement and pattern recognition. Later, Shibuya and Yanaka developed a system to quantify sinter structure using image analysis. According to this method, a TV camera and computer are used simultaneously to observe the sinter structure both macroscopically and microscopically. Sinter mineral phases (hematite, magnetite, calcium–ferrite, and slag) and pores are identified microscopically based on differences in brightness. Macroscopic observation allows the identification of an unmelted ore region, a pore region, and a sintered region formed by solid phase diffusion or by melting and subsequent solidification.

Table 1 summarizes the two systems for computer measurement of iron ore sinter. Jeulin’s system was developed by IRSID and the school of Mines of Paris. Yanaka’s system was developed by the University of Tokyo and Nippon Corporation. Both can quantify mineralogical components based on the threshold segmentation technique. Jeulin’s
system can also determine size distribution using the structural elements of various sizes and shapes. For automatic recognition, both determine the mineralogy phase based on the reflective powers, which can be determined from the brightness of the pixel in the image. The brightness of the image of the polished sinter section is determined by many factors, including the quality of the polished section, the technical parameters of the microscope, the working conditions of the CCD camera connected to the microscope, etc. If any one of these parameters changes, the brightness of the image also changes. For example, brightness increases as the intensity of the input light on the polished sinter section increases. The reliability of the reflective powers of the mineralogical phases in commercial sinter is, therefore, important. Industrial parameters such as sintering temperature or cooling speed affect the mineralogy phases, making them indistinguishable by brightness alone. The present authors have studied the relationship between the features of mineralogical phases and gray level histogram.\(^5\) Their previous work has shown that the mineralogy phases can be determined not only by the brightness of the image, but also by their textures. The texture features are influenced less by operational parameters. Other researchers have successfully used the gray-level co-occurrence matrix (GLCM) technique\(^5\) to determine the texture of rock\(^7\) or of the earth’s gravity field.\(^8\) This work uses the same technique to study the relationship between texture features and the mineralogy phases in iron ore sinter.

### 2. Methodology

#### 2.1. Gray-level Co-occurrence Matrix

A co-occurrence matrix, or co-occurrence distribution, defines the distribution of values co-occurring over an image at a given offset. Mathematically, a co-occurrence matrix \(C\) is defined over an \(M\times N\) image, with an offset \((\Delta x, \Delta y)\), as:

\[
C(i,j) = \sum_{x'=1}^{M} \sum_{y'=1}^{N} 1 \text{ if } (x,y) = i \text{ and } (x+\Delta x, y+\Delta y) = j \\
0 \text{ otherwise} \\
\]

\(.............(1)\)

where \(i\) and \(j\) are gray level, \(x\) and \(y\) are the coordinate of pixel, and \(M\) and \(N\) represent the number of rows and columns respectively. Equation (1) gives the probability of two pixels: Pixel \((x,y)\) with gray level \(i\) is the starting point. Another pixel \((x+\Delta x, y+\Delta y)\) occurs with gray level \(j\). The distance between the two pixels is \(\delta\), and the clockwise offset angle between the \(x\)-axis and the line connecting the two pixels is \(\theta\).

The four most common values for \(\theta\) are 0°, 90°, 45°, 135°. The set of co-occurrence pixels can be expressed as:

\[
R(i,j, \delta, \theta) = \{(x,y), (x+\Delta x, y+\Delta y)\} | f(x,y) = i, f(x+\Delta x, y+\Delta y) = j \\
\]

\(.............(2)\)

\[
R(i,j, \delta, 90^\circ) = \{(x,y), (x+\Delta y, y-\Delta x)\} | f(x,y) = i, f(x+\Delta y, y-\Delta x) = j \\
\]

\(.............(3)\)

\[
R(i,j, \delta, 45^\circ) = \{(x,y), (x+\Delta x, y+\Delta y)\} | f(x,y) = i, f(x+\Delta x, y+\Delta y) = j \\
\]

\(.............(4)\)

\[
R(i,j, \delta, 135^\circ) = \{(x,y), (x+\Delta x, y-\Delta y)\} | f(x,y) = i, f(x+\Delta x, y-\Delta y) = j \\
\]

\(.............(5)\)

Based on the GLCM, some statistical variables can be calculated. In order to compare these statistical variables across images of different sizes, The GLCM must be normalized as follows:

\[
p'(i,j) = P(i,j) / S = P(i,j) / \sum_{i=1}^{L} \sum_{j=1}^{L} P(i,j) \\
\]

\(.............(6)\)

where \(S\) is the sum of the elements in GLCM, \(L\) is the maximum gray level, and the size of the GLCM.

Contrast in an image can be expressed as:

\[
f_1 = \sum_{i=1}^{L} \sum_{j=1}^{L} (i - j)^2 \cdot p'(i,j) \\
\]

\(.............(7)\)

Contrast, or inertia moment, represents the articulation of an image. It is expected to be high if the texture is clearer and the rills of texture are deeper.

Energy, which measures the number of repeated pairs, can be calculated by:

\[
f_2 = \sum_{i=1}^{L} \sum_{j=1}^{L} p'(i,j)^2 \\
\]

\(.............(8)\)

Energy, also called angular second moment, represents the degree of homogeneity of gray distribution and the thickness of texture. The thicker the texture, the greater the energy.

Entropy, which measures the randomness of a gray-level distribution, can be expressed as:

\[
f_3 = -\sum_{i=1}^{L} \sum_{j=1}^{L} p'(i,j) \log_2 p'(i,j) \\
\]

\(.............(9)\)

Entropy represents the complexity of texture and degree of non-uniformity. It is expected to be high if the gray levels are distributed randomly throughout the image.

Inverse Difference Moment (IDM), measures the

<table>
<thead>
<tr>
<th>mineralogy phase</th>
<th>magnetite</th>
<th>hematite</th>
<th>fayalite</th>
<th>calcium silicate</th>
<th>calcium ferrite</th>
<th>pore</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\mu)</td>
<td>121.1</td>
<td>137.8</td>
<td>70.6</td>
<td>52.6</td>
<td>109.5</td>
<td>43.1</td>
</tr>
<tr>
<td>(\sigma^2)</td>
<td>34.0</td>
<td>19.6</td>
<td>67.9</td>
<td>47.5</td>
<td>128.7</td>
<td>10.9</td>
</tr>
</tbody>
</table>
smoothness of the image, and like homogeneity, can be expressed by:

\[ f_4 = -\frac{1}{L^2} \sum_{i=1}^{L} \sum_{j=1}^{L} \frac{p'(i, j)}{1 + (i - j)^2} \]  

(10)

The IDM is expected to be high if the gray levels of the pixel pairs are similar.

### 2.2. Pattern Recognition

There are many methods of pattern recognition; however, iron ore sinter has few mineralogy phases on which to base pattern recognition. These phases include hematite, magnetite, calcium–ferrite, slag, and pores. Complex pattern recognition methods such as neutral network, genetic algorithm, and supporting vector machines are not necessary to identify these phases. The present paper uses the simple supervised classification method instead. The sample space distance is calculated from the function of Canberra space distance:

\[ D_{ij} = \frac{1}{J} \sum_{j=1}^{J} \frac{|x_j - S_{ij}|}{x_j + S_{ij}} \]  

(11)

where \( x \) is the undetermined mineralogy phase, \( S \) is the related features of standard mineralogy in the database, \( i \) is the number of mineralrology phases in the database, the \( j \) is the number of features, and \( D_{ij} \) is the space distance between the mineralogy to be recognized and the standard mineralogy \( S_i \).

#### 2.3. Gray Level Histogram

The gray-level histogram, which is an important feature of an image, is an approximate expression of the density function of the gray level. It shows the occurrences of the gray level over an image. The histogram is described as:

\[ G_i = \sum_{m=1}^{M} \sum_{n=1}^{N} P(i, m, n) \]  

(12)

where \( M \) and \( N \) represent the total number of rows and columns, and \( G_i \) represents the occurrence of gray level \( i \). The definition of \( P(i, m, n) \) is expressed as:

\[ P(i, m, n) = \begin{cases} 1 & P(m, n) = i \\ 0 & P(m, n) \neq i \end{cases} \]  

(13)

Since the images may be different sizes, normalization is necessary. This is expressed as:

\[ G'_i = \frac{G_i}{M \times N} \]  

(14)

### 3. Extraction of Features from a Micrograph of Sinter

To use GLCM, the relationship between the features mentioned above and variables such as \( L, M, N, \theta, \) and \( \delta \) must be determined. Identification of the mineralogy phases by GLCM is valid only if the features used are steady and discriminable. From the definition of the GLCM, the parameters, \( L, M, N, \theta, \) and \( \delta \), determine the matrix, as well as the values of \( f_1 \) to \( f_4 \). Figure 1 is a typical micrograph of a polished sinter section, showing the corrosion structure of magnetite and calcium ferrite. It provides the basis for an analysis of the method presented here. To investigate the effect of texture on the features, Fig. 2 shows the same micrograph in a 4×4 grid.

#### 3.1. Features Dependent on Gray Levels

The gray-level image in Fig. 1 was transformed from a 24-bit RGB image, a size widely used in a 32-bit computer. The equation used for transformation is:

\[ I = \frac{1}{3} (R + G + B) \]  

(15)

where \( R, G, \) and \( B \) represent the red, green, and blue components of the pixel in a 24-bit bmp file, with eight bits for each component. The variable \( I \) is the gray level transformed. According to this equation, \( I \) also have eight bits, so the gray levels are \( 2^8 = 256 \). Figure 3 shows the gray-level histogram of Fig. 1.

According to this author’s previous work, which analyses the relationship between mineralogy features and the gray-level histogram, the distribution of the gray level in the histogram agrees with the law of normal distribution for each mineralogy phase. The parameters, such as average gray level \( \mu \) and variance \( \sigma^2 \) as listed in Table 1. The minimum difference of \( \mu \) between the mineralogy phases is about 9.5 (calcium silicate and pore). The difference between magnetite and calcium ferrite is 11.6, and that between magnetite and hematite is 16.7. Based on the discriminable gray level for these mineralogical phases, a gray level range from 16 to 256 was selected for this study. The temporary values of the remaining variables are: \( M = N = 15, \delta = 4, \theta = 0^\circ \). The computational results are shown in Fig. 4 through Fig. 7.

In Fig. 4, contrast dependent on gray level for the 16 image is plotted in the four subfigures. Contrast for images (1, 1), (1, 2), (2, 1), and (2, 2) in Fig. 2 is plotted in subfigure A of Fig. 4. In the same manner, images (1, 3), (1, 4), (2, 3), and (2, 4) are plotted in subfigure B, images (3, 1), (3, 2), (4, 1), and (4, 2) in subfigure C, and images (3, 3), (3, 4), (4, 3), and (4, 4) in subfigure D. These subfigures demonstrate that the contrast increases with an increase gray level. The rate at which contrast increases is different...
for every image. The contrast for image (3, 1) in subfigure C is the greatest of all 16 images. The average value of contrast for the four images in subfigure C is also the greatest among the four subfigures. Image (1, 4) has the lowest contrast, and subfigure B also has the lowest average contrast. Subfigures A and C have greater contrast than subfigures B and D. High contrast in texture means that the texture is clear and the texture rills are deep. As shown in Fig. 2, the details of texture are clear clearer in subfigures A and C than in subfigures B and D. Dots of magnetite scatter are clearly visible in the branches of calcium ferrite in subfigures A and C. The boundaries of the branches of calcium ferrite and the dots of magnetite are easily identified by the human eye. Pores in images (2, 1) and (3, 1) increase the contrast. Image (4, 1) has the second greatest value of contrast, and the small slag phase has the same effect on contrast as a pore. Images showing pores or slag phases, however, do not always show the greatest contrast. For example, image (1, 4) has the lowest contrast because the contrast is determined by both the area and the distribution of each phase. Generally, with more phases of varying gray levels, the texture shows greater contrast. Subfigures B and D are less clear, especially the zone of magnetite. Unlike the dots of magnetite in subfigures A and C, those in subfigures B and D are connected, making it difficult to distinguish the boundaries of the various phases. This texture will lower contrast, as shown in images (1, 4), (2, 4), (3, 4), and (4, 4).

These 16 images indicate that the level of contrast depends on the number of phases and their distribution. Figure 5 shows that the energy of the 16 images depends on the gray level. The decrease in energy with an increase in gray level is clear. The energy becomes constant when the gray level is higher than a critical value. Image (1, 4) has the highest energy, and images (2, 4), (3, 4), and (4, 4) have the higher energy. Subfigures B and D have greater average energy than subfigures A and C. Subfigure B has the greatest average energy. Image (3, 1) has the lowest energy, and images (4, 1), (2, 1), and (2, 2) also have lower energy. Energy reflects the degree of homogeneity of the gray distribution and the thickness of the textures. Because there are no clear boundaries between the phases, large areas of subfigures B and D join in a single broad texture. Thus subfigures B and D have the greatest energy. Except for its pore zone, image (1, 4) is covered with magnetite. Given this texture, the energy (0.0089) is greater than that in other images. The same phenomenon appears in images (2, 4), (3, 4), and (4, 4). Compared with image (1, 4), image (4, 4) shows slight texture in some local zones, and thus low energy (0.0048). Image (2, 1) has the narrow regions of texture and the gray level is distributed randomly, so that it has low energy (0.0013). Image (3, 1) also has a narrow region of texture and many small dots of magnetite broadly scattered. This texture has lower energy.

Figure 6 shows the relationship between entropy and the number of gray levels. For each image, entropy increases as the number of gray levels increases, and it will become constant when the number of gray level exceeds a critical value. Subfigures A and C have higher entropy than subfigures B and D. The entropy for images (2, 1), (2, 2), and (1, 2) are very close, even overlap, indicating that these three images have similar texture. So are the images (4, 1) and (3, 2), and images (3, 3) and (3, 4). Image (2, 1) has the highest entropy, whereas, image (1, 4) has the lowest en-
tropy. These analyses reveal that the texture of magnetite has low entropy and calcium ferrite has high entropy.

Figure 7 shows that IDM depends on the number of gray levels. The IDM for each image decreases as the number of gray levels increases. The values of IDM will become constant when the number of gray levels exceeds a critical value. Subfigures B and D have higher IDM than subfigures A and C. The average values of IDM for images in subfigure A are very close, especially those for images (1, 1) and (1, 2). Image (2, 1) and (2, 2) even overlap. The IDM of images (4, 4), (3, 4), (3, 3), and (4, 3) in subfigure D are close to one another. Image (1, 4) has the highest IDM (0.27), followed by image (2, 4), which has an IDM of 0.20. These high IDM levels are due to the homogeneity of the 15 pixels in the left top are the pore zone and the gray level of these pixels is very similar (about 39–41). In image (2, 4), the 15×15 pixels in the left top are the magnetite; no other mineralogy phases are mixed. In image (3, 1), the 15×15 pixels in the top left are the zone of magnetite mixed with calcium ferrite and slag phase. This image, therefore, has the lowest IDM (0.05). The same characteristics explain the IDM levels in image (4, 1), (2, 2), and (2, 1).

These observations indicate that energy, entropy, and IDM change little when the gray level is over 100. This stability is necessary for pattern recognition; therefore, the present paper used $L=125$ in the analysis of other parameters.

3.2. Features Depend on the Size of Image Window

In GLCM, the size of the image window is important for accurate feature extraction. If the image is too big, it may consume too much computational time. On the other hand, if it is too small, it may not sufficiently extract the texture.

The size of Fig. 1 is 768×576 pixels. Once divided into 16 images, the size of each image is 192×144 pixels. To investigate the features dependent on the size of the image window, the range of 15–140 was selected for $M$ and $N$. Further, $L$ was fixed at 125, $\delta$ at 4, and $\varphi$ at 0°. The features dependent on the size of the image window are plotted in Fig. 8 through Fig. 11.

In Fig. 8, the contrast decreases when the size of the image window is enlarged, and it becomes more stable with a large image window. Subfigures A and C have greater average contrast than the other two subfigures. Image (3, 1) has the greatest contrast (153), and image (1, 4) has the lowest. The difference in contrast between the small image window and large image window is minimal for images (4, 2), (4, 4), and (3, 4), indicating that contrast in these images changes little when the size of the image window is enlarged. This small difference also means that the basic texture elements in these three images is very small, about
The contrast in images (1, 2), (1, 3), (2, 1), (2, 2), (3, 1), (3, 2), and (4, 1) changes dramatically when the size of the window increases from 15 to 75. Beyond 75 pixels, the contrast becomes relatively stable, meaning that the smallest basic texture elements should be about 75–85. In the mineralogy phase, the texture of calcium ferrite mixed with magnetite and some slag phase is complex, therefore, the contrast will be stable only if the image window is big enough.

As shown in Fig. 9, the energy for each image decreases as the size of the image window increases, but it changes little when the image is big. The energy of images (1, 4) and (3, 4) decreases quickly when the size of the image window increases from 25 to 40. The energy of images (4, 1), (4, 3), and (2, 1) changes less as the size of the window increases. The energy of images in subfigures B and D is higher than that in subfigures A and C. Image (1, 4) has the highest energy, and image (4, 1) has the lowest, indicating that a large area of magnetite or pore can increase the energy of the image. Calcium ferrite, which has a branch structure, can decrease the energy of the image. The small area of slag phase and pore distributed in the calcium ferrite or magnetite can reduce the energy of the image.

Figure 10 shows that entropy increases as the size of the image window increases. When the image window is over 75 pixels, entropy becomes relatively steady. The entropy of image (4, 1) is the greatest (9.99), and that of image (1, 4) is the smallest (7.86). The images in subfigures A and C have high entropy, and those in subfigures D, and particularly B, have low entropy. These values indicate that the texture of calcium ferrite has high entropy because the gray level is distributed more randomly than in magnetite and pore.

Figure 11 shows the relationship between IDM and the size of the image window. This relationship is complex. The IDM of images (2, 2), (1, 4), (2, 3), (2, 4), (4, 2), (3, 4), and (4, 4) decreases as the size of image window increases. That of the other images, however, increases as the size of the image window increases. When the size of the image window is larger than 75 pixels, the value of IDM changes less as the image window is enlarged. The IDM of image (3, 3) remains steady when the size of image window changes from 40 to 140. Images in subfigure A have similar IDM, fluctuating around 0.2. Although the IDM of images in subfigure C varies greatly when the size of the image window is small (<75 pixels), that variation is much reduced when the image window is larger, also finally approaching 0.2. The IDM of the images in subfigure B is higher than others; that of images (2, 3) and (1, 3) is almost in superposition when the image window is large. Except for image (1, 4), which has the highest IDM (0.4) and
image (4, 3), which has the lowest (0.23), all images in subfigures B and D have similar IDMs, changing from 0.26 to 0.32. The texture of calcium ferrite appears to have low IDM. That of magnetite has a high IDM, and the large pore area enlarges the IDM of the texture.

This analysis suggests that contrast, energy, entropy, and IDM change less when an image window is over 75 pixels; therefore, the reminder of this paper is based on an image window size of 100×100.

### 3.3. Features Dependent on the Distance of the Co-occurrence

Distance between the co-occurrences, \( \delta \), indicates how far apart the pixel pair occurs. The present paper uses a range of 1–30 for \( \delta \). The results are shown in Fig. 12 through Fig. 15.

In Fig. 12, contrast increases as the distance between co-occurrences increases. When \( \delta \) is smaller than 5, the contrast increases dramatically. Image (3, 1) has the highest contrast, and image (2, 4) has the lowest. The contrast of images in subfigures A and C is higher than that in subfigures B and D. When \( \delta \) is over 15, the contrast becomes steady, except in images (1, 4), (3, 1), and (4, 3). The contrast of the texture of calcium ferrite is higher than that of magnetite, changing from 190 to 230 when \( \delta \) is over 15. The texture of magnetite has low contrast, changing from 40–120. If some calcium ferrite and pore mix, contrast will increase to 150–170.

In Fig. 13, energy decreases as the distance between co-occurrences increases. When the distance between co-occurrences is over 10, the energy becomes constant. When \( \delta \) is over 25, image (1, 4) has the highest energy (0.0145), whereas images (3, 1) and (4, 1) have the lowest energy (0.0013). The images in subfigure B have the highest energy; those of subfigure C have the lowest. In general, the texture of magnetite has higher energy, changing from 0.004 to 0.009, whereas the texture of calcium ferrite has lower energy, changing from 0.0013 to 0.0036. The pores scattered in these textures increase the energy of the texture.

In Fig. 14, entropy increases as the distance between co-occurrences increases. When \( \delta \) is over 10, entropy becomes steady. When it is over 20, image (3, 1) has the highest entropy, whereas image (2, 4) has the lowest (7.4). These values indicate that the texture of calcium ferrite has higher entropy, changing from 8.9 to 10.2, whereas the texture of
magnetite has lower entropy, changing from 8.1 to 8.4. Pores will reduce the entropy of the texture.

In Fig. 15, IDM decreases as the distance between co-occurrences increases. When \( \delta \) is over 10, IDM is steady. Image (1, 4) has the highest IDM (0.258), whereas image (4, 1) has the lowest (0.091). The texture of calcium ferrite has low IDM, changing from 0.09 to 0.15, whereas the texture of magnetite has high IDM, changing from 0.15 to 0.25. The effect of pore on IDM here is interesting; in calcium, it appears to reduce IDM, but in magnetite, it appears to increase IDM. According to Eq. (4), IDM should be determined by the difference in gray level of the mineralogical phases, and the distance between co-occurrences used in the GLCM.

This analysis demonstrates that contrast, energy, entropy, and IDM become steady when the distance between co-occurrences is over 10. The remainder of this paper assumes a distance between co-occurrences of \( \delta = 15 \).

3.4. Features Dependent on the Offset Angle

The offset angle, \( \theta \), represents the direction of texture growth. Contrast, energy, entropy, and IDM dependent on the four offset angles are shown in Fig. 16 through Fig. 19.

In Fig. 16, the contrast for 135° stands out from the others. The contrast for 45° and 90° is similar; in the same position, the contrast in 45° is only slightly higher than that in 90°. As for the mineralogy phases, calcium ferrite has low contrast, magnetite has high contrast, and pores can increase contrast. A comparison of these contours with the micrograph in Fig. 1 indicates that the contours of contrast in 0°, 90°, and 45° can easily represent the general zone of Fig. 1. The zones of magnetite, calcium ferrite, and pores

Fig. 16. Dependence of contrast on offset angles.

Fig. 17. Dependence of energy on offset angles.

Fig. 18. Dependence of entropy on offset angles.

Fig. 19. Dependence of IDM on offset angles.
can be identified from these contours. In Fig. 17, the energy for 0°, 90°, and 45° is similar. The various mineralogy phases can also be easily identified from these contours. The contour of energy in 135° looks somewhat different from the others. Therefore, it means the average energy of the four offset angles is necessary for recognition.

The contours of entropy in Fig. 18 and the contours of IDM in Fig. 19 have some of the same features apparent in Figs. 16 and 17. The entropy in 135° is somewhat different from that in other angles. To use these features as references for pattern recognition, they must be relatively constant. Because the direction of the texture in the micrograph is random in practice, this paper uses average features in all offset angles. According to the average values, the features of the main mineralogy phases can be summarized in Table 2.

### Table 2. Features of the primary mineralogy phases.

<table>
<thead>
<tr>
<th>Features</th>
<th>More calcium ferrite</th>
<th>More magnetite</th>
<th>Influence of pore</th>
</tr>
</thead>
<tbody>
<tr>
<td>Contrast</td>
<td>100-160</td>
<td>50-100</td>
<td>Enlarge</td>
</tr>
<tr>
<td>Energy</td>
<td>0.004-0.006</td>
<td>0.006-0.11</td>
<td>Enlarge</td>
</tr>
<tr>
<td>Entropy</td>
<td>8.4-9.1</td>
<td>7.2-8.3</td>
<td>Lesser</td>
</tr>
<tr>
<td>IDM</td>
<td>0.13-0.16</td>
<td>0.18-0.22</td>
<td>Enlarge</td>
</tr>
</tbody>
</table>

4. **Validation**

A second micrograph was used to validate the method developed here. This micrograph was also divided into 16 small images in Fig. 20. The four features were calculated for the four offset angles, with the following assumptions: \( L=125, M=N=100, \) and \( \delta=15. \) Averaging the features in four angles gives the final features. Equation (11) calculates the space distance between the images in Fig. 20 and those in Fig. 2. The image in Fig. 2 with the shortest space distance to the image to be analyzed is the pattern image recognized. The patterns identified, as well as the space distance between the objective image and the pattern image which was calculated using Eq. (11), are shown in Table 3.

Images (1, 1), (1, 2), and (2, 3) in Fig. 20 were found to be similar to image (4, 1) in Fig. 2. Images (2, 1), (3, 1), and (4, 1) in Fig. 20 were found to be similar to image (3, 1) in Fig. 2. Images (1, 3) and (2, 2) in Fig. 20 are similar to image (4, 3) in Fig. 2, and so on. All results proved accurate except those for images (1, 4), (3, 2), and (4, 2) in Fig. 20. The probable reason for errors in image (3, 2) and (4, 2) is the large slag phase with branch structure in the texture; no other image in Fig. 2 has a similar texture. If the image database of the mineralogical phases in iron ore sinter is sufficiently comprehensive, pattern recognition will be accurate. The reason for the error in image (1, 4) is also unclear, but likely due to the large pore area. The effect of the pore on the feature of the mineralogical textures should be studied systematically.

5. **Conclusion**

(1) Texture features such as contrast, energy, entropy, and IDM can function as references for pattern recognition, based on the GLCM.

(2) For the micrograph studied here of mineralogical phases in iron ore sinter, when \( L=125, M=N=100, \) and \( \delta=15, \) the GLCM provides a relatively constant feature.

(3) When the average features in four offset angles are used as a reference, and the Canberra space distance is cal-
Table 3. The patterns recognized for images in Fig. 20.

<table>
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<tr>
<th>Objective image</th>
<th>Pattern image</th>
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<th>Pattern image</th>
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<td>No.</td>
<td></td>
<td>No.</td>
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REFERENCES
3) D. Jeulin: Ironmaking Steelmaking, 10 (1983), No. 4, 145.