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Quantifying the Texture of Coal Images with Different Lithotypes through Gray-Level Co-Occurrence Matrix

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ABSTRACT

The Coal Pillar Rib Rating (CPRR) technique has been developed to assist in rib support design in underground coal mines. One major challenge of the data collection process is the measurement of coal strengths in the field. Schmidt hammer has been verified as a useful tool to determine coal strength. An alternative approach is to obtain the representative strength of coal mass by determining the coal lithotypes in the field based on the coal brightness profile by experienced geologists or mining engineers. In this paper, image processing techniques have been used to quantify the texture of coal images of different lithotypes with the purpose of classifying coal lithotypes. The coal images were collected from the pillar ribs with exposed surfaces in underground coal mines, and the coal lithotypes were identified when taking the images. The method of Gray-Level Co-Occurrence Matrix (GLCM) was used to analyze the textures of coal images of different lithotypes, and the texture parameters, such as contrast, homogeneity, energy, and entropy, were compared. The results show that the images of coal with different lithotypes have different textures, which can be quantified through the image processing. The results from this study demonstrate the potential of classifying coal lithotypes using rib photos and easing the data collection process of CPRR.

BACKGROUND

Coal ribs, which are the walls of coal pillars intentionally retained during mining to support overlying rock strata, play a crucial role in maintaining the structural integrity of underground coal mine excavations. The occurrence of rib falls presents severe safety risks, encompassing injuries, fatalities, and equipment damage. Researchers from the National Institute for Occupational Safety and Health (NIOSH) have been working on the development of an engineering-based approach for coal rib stability analysis and support design.

NIOSH researchers have developed the Coal Pillar Rib Rating (CPRR) technique to quantify the bearing capacity of coal pillar ribs (Mohamed et al. 2020). The CPRR technique considers homogeneity, strength, bedding condition, rock parting condition, face cleat orientation with respect to entry direction, and coal unit thickness. The calculation of CPRR requires various input parameters that need to be measured in the field, like the number of coal units, the thickness and strength of each coal unit, and the thickness and strength of rock partings that separate a rib into different coal units. One of the major challenges for the data collection process of CPRR is the determination of coal strengths in the field, and Schmidt hammer has been used as an indirect tool to determine coal strength (Rashed et al.

2018). An alternative approach is to obtain the representative strength of coals by determining the megascopic coal lithotypes in the field based on the coal brightness profile by experienced geologists or mining engineers.

Stopes (1919) was the first researcher to introduce the concept of the megascopic coal lithotype identification with the lithotype nomenclature. Traditionally megascopic character in banded bituminous coal is described compositionally in terms of the abundance and distribution of the four macro-lithotypes: vitrain, clarain, durain, and fusain. Over the years, other coal description systems based on the varying degrees of visible coal brightness and banding were developed from Stope's work. A simpler terminology and approach have been adopted in Australia, which uses the terms bright, banded, dull and fibrous, with designations for banded bright and banded dull. The use of the coal brightness methodology has gained widespread acceptance in Australia. The brightness profile logging of coal core is an accepted standard and is universally performed at Australian mines. However, such a system of logging coal core is not widely used in the United States. Rusnak (2017) conducted a total of 1,000 uniaxial compressive strength tests and 440 indirect tensile strength tests on cores that were collected from southern West Virginia and were logged with the megascopic coal lithotype nomenclature. The statistical analysis shows that the mechanical properties are correlated to the lithotype. The correlation between coal strength and megascopic coal lithotype was further confirmed by Rashed et al. (2018) when using Schmidt hammer to estimate the intact coal strength. The representative strength for bright coal, banded bright coal, banded dull coal, and dull coal was estimated in the study, making it convenient to determine the intact coal strength.

However, the megascopic coal lithotype is normally determined by geologists or mining engineers in the field or based on drilled cores. A number of problems arise from these manual methods and the most important one is the error from operator subjectivity. In order to overcome this problem, Yu et al. (1997) employed a window filtering method to analyze coal textural information acquired from banded bituminous coal seams in the field. They tried to discriminate the coal lithotypes accurately and automatically by conducting statistical analysis on the sliding windows captured from the coal images. However, there are significant developments in photography technology and image processing technique in the last two decades. The purpose of this study is to use the advanced image processing techniques to characterize megascopic coal lithotypes based on the study of Yu et al. (1997).

As pointed out by Rashed et al. (2018), the coal brightness profile infers a measure of volumetric cleat density, where bright coal (BC) is characterized with fine cleat spacing on the millimeter scale, and dull coal (DC) has wider cleat spacing on the centimeter scale. Due to the presence of dense cleats, it can be expected that the pixel values change frequently and regularly, and that the difference in cleat density is potentially reflected in the variation of pixel values. Thus, it is reasonable to select an image processing technique describing the relationship between pixels for the textural analysis and lithotype classification. The gray level co-occurrence matrix (GLCM) is such a method that is widely used to describe image texture/patterns and to extract features that are useful in various image processing tasks such as image segmentation, classification, and feature extraction. Texture refers to the visual properties that describe how rough, smooth, or patterned an area appears within an image. GLCM is used to characterize and quantify the texture or patterns in an image. The GLCM method has been used to classify coal and rock where anthracite coal and shale blocks were collected from an underground coal mine and photos were taken in the laboratory and analyzed with the GLCM method (Sun and Su 2013). Singh et al. (2019) analyzed six different rock micro-CT images with GLCM and revealed that every rock has its own GLCM signature depending on the typical variations of the gray-level intensities.

GLCM INTRODUCTION AND APPLICATION

GLCM Introduction

GLCM is a statistical method of examining the image texture considering the spatial relationship of pixels. It is also known as the gray level spatial dependence matrix, a matrix that is defined over an image to be the distribution of the co-occurring pixel values at a given offset. In simple terms, a GLCM is a 2-dimensional matrix that contains information about how often a pair of pixels with a specific intensity (or "gray level") appear in a certain orientation relative to each other in an image. The orientation is specified by a direction angle, such as 0, 45, 90, or 135 degrees, and the specific gray level values for the pixel pair are used as indices in the matrix. The value stored in the matrix at a given gray level is the number of times the pair appears in the specified orientation. Statistical measures can then be extracted from the matrix, including contrast, correlation, dissimilarity, energy, and homogeneity.

Contrast: measures the local variations or differences in intensity between neighboring pixels. It is calculated as the sum of squared differences between intensity levels in the GLCM. A high contrast value indicates that neighboring pixels have significantly different intensity values, resulting in a texture with sharp transitions and well-defined boundaries between different regions in the image. On the other hand, a low contrast value indicates that neighboring pixels have similar intensity values, suggesting a smoother and more uniform texture. Contrast is particularly useful in identifying textures with strong edges and fine details.

Correlation: measures the linear relationship between intensity levels in the image. It is calculated as the covariance of the intensity levels in the GLCM divided by the product of their standard deviations. A high correlation value indicates that the pixel intensities change linearly with respect to the distance and direction in the image, and the texture appears more ordered and regular in the image. On the other hand, a low correlation value indicates a weaker linear relationship between pixel intensities. This implies that neighboring pixels have less linear dependence, and the texture appears more random and disordered in the image. It provides information about the regularity and orientation of textures in the image.

Dissimilarity: measures the average difference in pixel intensities between neighboring pixels. It is calculated as the sum of the absolute differences between gray levels of pixel pairs, weighted by the frequency of occurrence of those pixel pairs in the GLCM. A high dissimilarity value indicates that neighboring pixels have significantly different intensity values. This means that the texture in the image appears more diverse and has sharp transitions between pixel intensities. Dissimilarity is particularly useful in capturing the level of contrast and variation in the texture of an image. It should be noted that both contrast and dissimilarity provide information about the variations in gray levels within an image; however, they do so in slightly different ways. Dissimilarity focuses on the absolute differences between gray levels in co-occurring pairs and is suitable for identifying coarse textures, while contrast emphasizes the squared differences between gray levels in co-occurring pairs, which tends to highlight variations in fine details and local contrast within the texture.

Energy: measures the uniformity or regularity of the GLCM. It is also known as Angular Second Moment (ASM) and is calculated as the sum of squared elements of the GLCM. A high energy value implies that neighboring pixels tend to have similar intensity values, resulting in a smoother and less textured appearance in the image.

Homogeneity: measures the closeness of the distribution of elements in the GLCM to the main diagonal. It is calculated as the sum of the products of each gray level pair divided by 1 plus the square of their difference. A high homogeneity value implies that neighboring pixels tend to have similar intensity values, resulting in a more regular and smooth texture appearance in the image. On the other hand, a low homogeneity value indicates that neighboring pixels have diverse intensity values, indicating a more complex and heterogeneous texture in the image.

GLCM Application Example

The classification of coal and shale with GLCM features is taken as an example to demonstrate the effectiveness of GLCM in capturing different image textures. Due to the variations in composition and sedimentary environment, coal and shale have distinct differences in textures (Xue, 2022). It can be expected that there are significant differences in the calculated GLCM features. As shown in Figure 1, part of a rib image with coal and shale was extracted with 500 pixels along each side was used for the demonstration. Small patches with a side length of 50 pixels were extracted from coal and shale. Four patches were extracted from shale and coal, respectively, resulting in a total of 8 patches. The location of the patches is marked on the rib image, and the enlarged view of the patches are displayed separately in Figure 1. It can be found with naked eyes that the images for coal and shale are different. The color for shale images is mainly gray or dark gray and the whole images look smooth, while the color for coal images is mainly black and white (brightness) and the white spots are surrounded by the black. At some edges, there are sharp changes in the color. How will the difference in image textures represent in the calculated GLCM features? GLCM features were then calculated along the horizontal direction for each patch, and the results are summarized in Figure 1 with correlation and dissimilarity as an example. It can be observed that the shale images have lower dissimilarity and correlation levels than the coal images, making the data points for shale concentrated at the lower left corner. The way that the data is spread makes it easy to classify shale and coal.

The above analysis with coal and shale demonstrates the power of the GLCM method in capturing the differences in the image texture between coal and rock. However, it can be found from the enlarged views of patches in Figure 1 that there are distinct differences in the image textures between coal and shale. The next question will be whether the method can be used to classify different coal lithotypes based on the texture. It can be expected that there will be no such distinct difference as shown in Figure 1, and it will need more detailed textures to classify coal lithotypes.

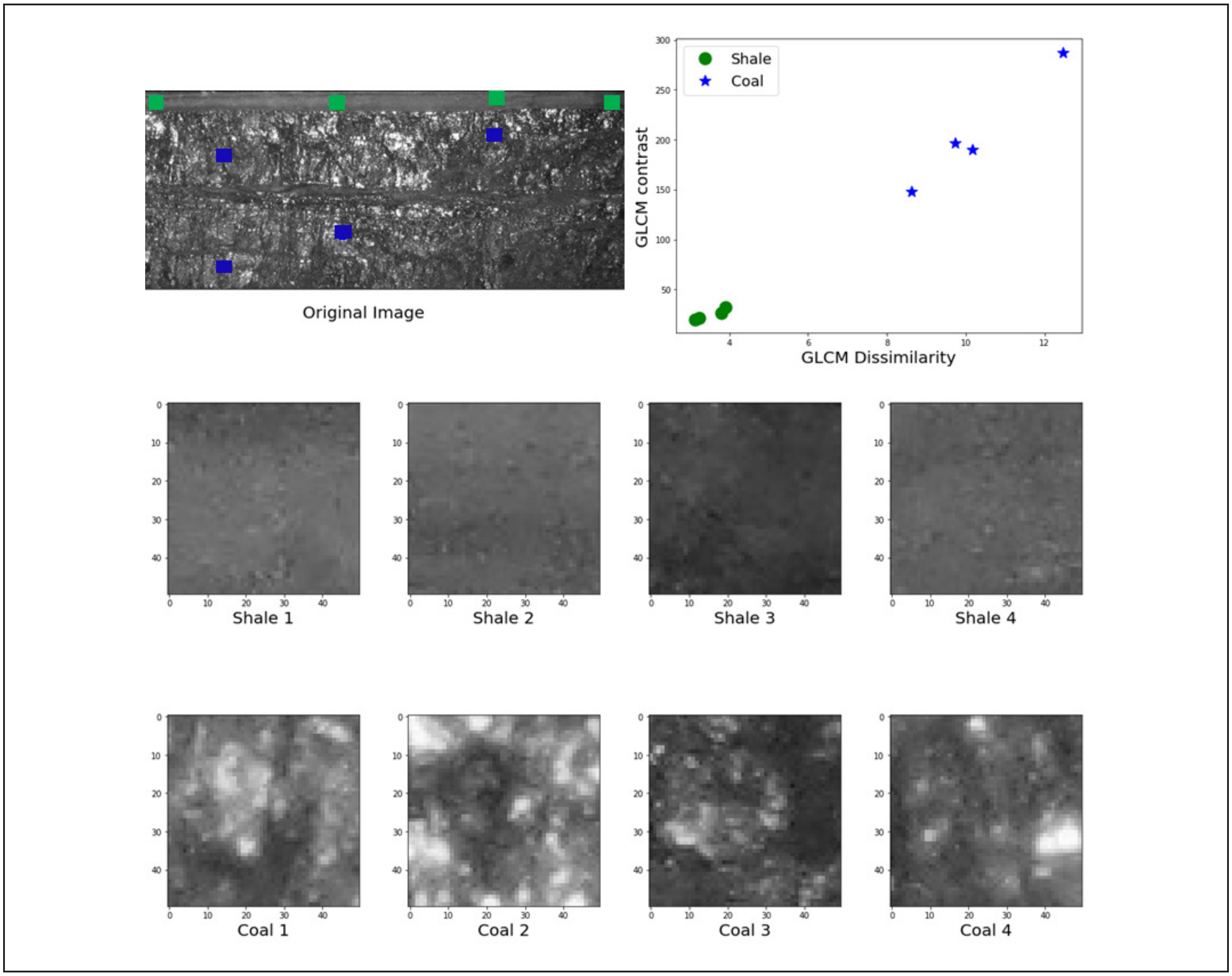


Figure 1. An example application of GLCM to classify coal and shale on a rib image

GLCM FEATURES FOR DIFFERENT COAL LITHOTYPES

In order to control rib failures in underground coal mines, NIOSH is developing a stability analysis and support design tool for coal pillar ribs. Rib photos have been taken by NIOSH researchers during the extensive field trips for rib surveys in underground coal mines in the U.S. Most of the ribs are either weathered or covered with dust and sealant, which significantly affects the color and textures. In order to obtain the representative features, the areas with fresh surface within the rib photos were selected for this study. The fresh surfaces are not newly mined coal pillar ribs but are fresh failure surfaces after rib spalling. Two rib fresh surfaces were selected, one for BC and the other one for banded bright coal (BBC). For each selected rib fresh surface, multiple photos were taken with different camera settings.

The photos for BC were taken in an underground coal mine in Virginia. As an example, the cropped image taken under a specific camera setting is shown in Figure 2 (a). The width and height of the image are 1,773 and 1,349 pixels, respectively, and the width of covered area is 330 mm (13 inches). The fresh surface for BBC was selected in an underground coal mine in Illinois. An example of the cropped image is shown in Figure 2(b), which was taken with the same camera settings as the BC image. The width and height of the cropped image are 4,424 and 1,761, respectively, and the width of the covered area is 914 mm (36 inches).

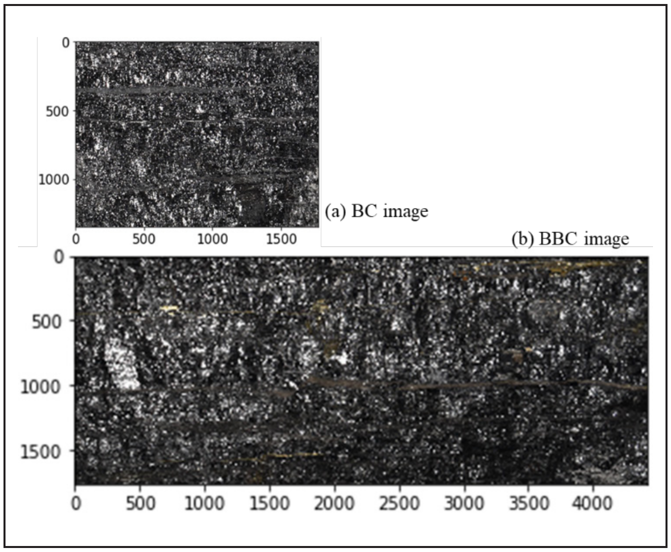


Figure 2. Images of coal with different lithotypes extracted from rib photos

GLCM features with the same camera settings

The two coal images shown in Figure 2 were used for the analysis in this section. They were shot with the same camera settings with only one difference, which is the focal length, the distance between camera and the coal ribs. Capturing an image from a closer distance will cause the scene or object to occupy more pixels, resulting in a higher resolution with finer details. GLCM is a texture analysis method that depends on the spatial relationships between pixel values in the image. When the coal images of different resolutions are used, the spatial relationships between pixel values change, and different GLCM features can be obtained. Therefore, it is necessary to resize the images to the same resolution for comparison. In a previous study (Yu et al., 1997)methods for its characterisation and analysis are poorly developed. Banding texture was obtained manually from the coal face and core at a minimum resolution of 1 mm. Window filtering was used to determine the optimum resolution (30–50 mm, coal rib images were used to classify coal lithotypes and it was found that a minimum resolution of 1 pixel/mm (25 pixels/in) is necessary for the successful classification. Thus, all the coal images were resized based on this resolution for the analyses in this section. The detailed investigation of the influence of resolution on GLCM statics will be presented in next section.

Rather than using the whole image as one input for GLCM calculation, small patches or sliding windows were randomly extracted from the original image and were used for GLCM calculation. Three patch sizes are used, namely 25×25 pixels, 50×50 pixels, 100×100 pixels, corresponding to the covered areas of 25×25 mm, 50×50 mm, and 100×100 mm, respectively. For each patch size, 100 patches were randomly extracted from each image in Figure 2. In such a way, a database of GLCM features with different coal lithotypes can be generated for statistical analyses. Besides patch size, there are other parameters, namely angle (or direction) and distance (or offset), potentially affecting the calculated GLCM features. The influence of these parameters on GLCM features of coal images of different lithotypes are studied in this section.

With GLCM method, the angle specifies the direction in which the co-occurrence is calculated. Common angles are 0 degree (horizontal), 45 degrees (diagonal), 90 degrees (vertical) and 135 degrees (the opposite diagonal). Different angles capture texture patterns along different directions. The box plot of various GLCM features along horizontal (0 degree) and vertical (90 degree) directions is shown in Figure 3, and all the other parameters were kept the same. The patch size is 50×50 pixels, and a distance value of 1 is used. First of all, the box plots were compared between BC and BBC. It can be found that, for any GLCM feature, there are observable differences in the median values. Compared to BBC, the textures of BC have higher contrast and dissimilarity levels on average, indicating that the image texture of BC has large local variation in pixel intensities, resulting in sharp transitions. At the same time, the textures of BC show generally lower correlation, energy, and homogeneity levels than those of BBC, indicating that

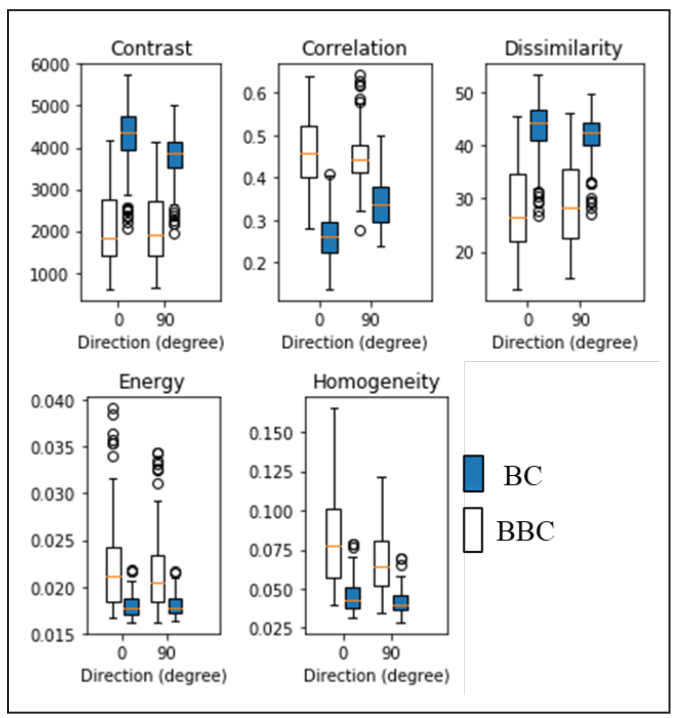


Figure 3. Box plots of various GLCM features along two different directions (horizontal and vertical)

BC images have more random, diverse, and heterogeneous textures. As stated by Rashed et al. (2018)which are expensive and time consuming. The research work outlined in this paper examines the use of indirect strength estimation methods-the point load test (PLT, BC has denser cleats than BBC. It can be expected that, due to the denser presence of cleats, there is more frequent change in the brightness in the images of BC than those of BBC, potentially leading to higher contrast and dissimilarity levels and lower correlation, energy, and homogeneity levels. The results confirm that the GLCM method can capture the differences in the brightness profile between BC and BBC through textural analyses. In addition, all the GLCM features for BC, except the correlation along vertical direction, have a smaller spread of values, indicating that the GLCM features for BC are tightly clustered and the textures tend to be more consistent than that of BBC.

Furthermore, the GLCM features were compared between different directions. It can be found that, regardless of the coal lithotype, there is no substantial difference in the GLCM features observed between the horizontal and vertical directions. This suggests that the textural properties of the images of BC and BBC exhibit a remarkable level of symmetry or similarity along these two directions. Since there are no significant differences in the GLCM features calculated along the horizontal and vertical directions, the GLCM features calculated along the horizontal direction were used for all of the following analyses.

With the GLCM method, the distance refers to the pixel distance between the reference pixel and the neighboring pixel for which co-occurrence is measured. Common distance values include 1, 2 and 3 pixels. Different distances measure different levels of texture information, and larger distances capture longer-range texture patterns. Distance values of 1, 2, and 3 were used to investigate the influence of distance on the calculated GLCM features. Figure 4 shows the box plots of various GLCM features with different distance values, and the patch size is 50×50 pixels. When altering the distance value, there are variations, whether significant or subtle, observed in all the GLCM features regardless of the coal lithotype. The trend in variations with distance is consistent for both BC and BBC across all features. As the distance value increases, contrast and dissimilarity increase. This is because larger distance encompasses pixel pairs with greater intensity variations, which are reflected in higher contrast and dissimilarity values. On the contrary, correlation, energy and homogeneity decrease with the increase in distance value. As the distance increases, the GLCM includes pixel pairs that are farther apart, and the correlation tends to decrease because they are

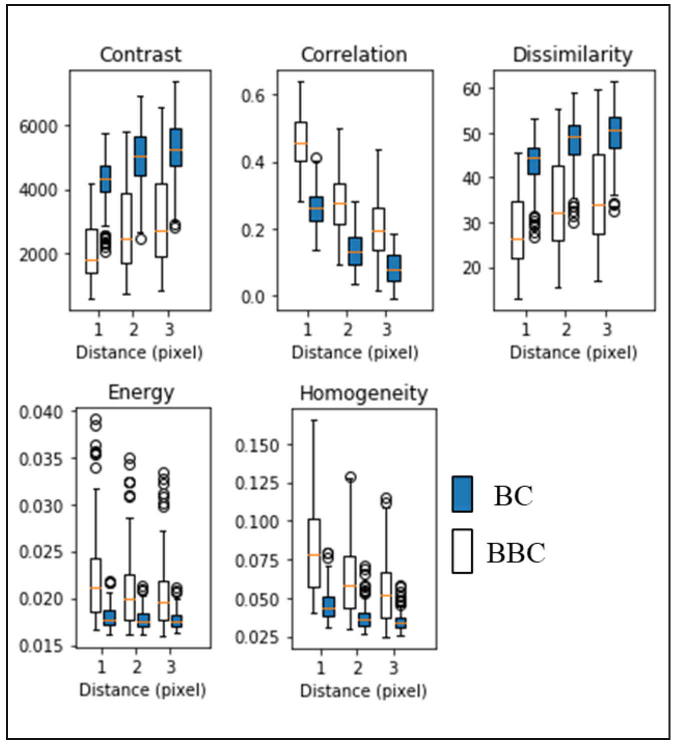


Figure 4. Box plots of various GLCM features with different distance values

less likely to exhibit strong linear dependencies; at the same time, there is a higher likelihood of encountering pixel pairs with larger differences in gray levels, which can lead to the decrease in homogeneity. Energy decreases or remains relatively constant, indicating the texture becomes more heterogeneous or irregular with increasing distance.

In addition, each GLCM feature was compared between BC and BBC. It can be found from the median value and the spread of the data that, although there are still differences in two groups of data, the distribution of these groups of data become closer with the increase in distance value. This makes them difficult to classify, which is not preferable. Thus, a distance value of 1 was selected for the following analyses.

Patch size is another factor affecting the calculated GLCM features. The patch size determines the scale at which texture features are extracted, and this can affect the sensitivity to different texture patterns. Larger patch sizes capture texture patterns at a coarser scale while smaller patch sizes capture finer details. Smaller patches can be more sensitive to noise, and larger patches can provide a more stable texture analysis by averaging out noise. Larger patches incorporate more contextual information, potentially providing a better understanding of global texture patterns, while smaller windows focus on local details. Thus, it is a trade-off. Larger patches offer more context

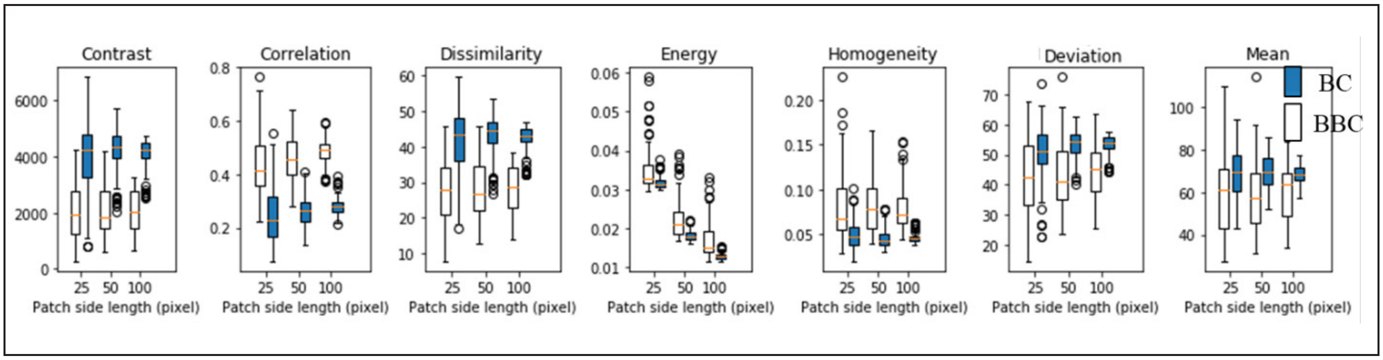


Figure 5. Box plots of various GLCM features with varying patch sizes

but may lose sensitively to fine detail, while smaller patches capture finer details but may miss global patterns. The influence of patch size on GLCM features was investigated in this section and the results are shown in Figure 5. It is observed from the median values that, except energy, the GLCM features for BC and BBC show negligible influence by patch size. However, the spread of the data, regardless of the coal lithotype and GLCM features, decreases with the increase in patch size, indicating more consistent texture patterns with the increasing patch size. As mentioned earlier, the selection of patch size will be a trade-off. The patch size selection should focus on the fine detail of the images without completely ignoring the global patterns. Also, a side length of 30–50 mm for a sliding window was found to obtain the best results for megascopic coal lithotype classification in a previous study (Yu et al. 1997)methods for its characterisation and analysis are poorly developed. Banding texture was obtained manually from the coal face and core at a minimum resolution of 1 mm. Window filtering was used to determine the optimum resolution (30–50 mm. This corresponds to the patch size length of 50 pixel in Figure 5 based on the resolution. Thus, a patch size of 50×50 pixel or mm was selected for the following analyses.

With the recommended minimum resolution in a previous study, the influence of various parameters for GLCM calculation was investigated with the purpose of optimizing the parameters. Based on the above analyses, an angle value of 0 degree, a distance value of 1, and a patch size of 50×50 mm was determined and were used for the following statistical analyses in this section. Besides the GLCM features, the common statistics, mean and standard deviation, are included in the statistical analysis. When the coal images are converted into gray, they can be treated as 2D arrays of pixel intensity values and mean, and standard deviation can be easily calculated.

A pairplot of the image features are shown in Figure 6. It shows the pairwise relationship in the dataset by mapping different features of the dataset onto a column and row in a grid of subplots. The data were plotted with different colors based on the megascopic coal lithotype. Bivariate distributions were drawn with kernel density estimation (KDE) in the lower triangle, and pairwise scatter plots were drawn in the upper triangle. The correlation coefficients between each pair of features were calculated and marked in the upper triangle. Along the diagonal, univariate distribution plots with KDE were drawn to show the marginal distribution of the features in each column based on the coal lithotype.

A few observations can be made from the KDE plots along the diagonal. The first thing observed is that, for each feature, the central peaks for different coal lithotypes locate at different locations, indicating the difference in values on average. Second, all the features for BC have narrower distributions and higher peaks than those of BBC, indicating that the BC features have lower variation and are more concentrated. Third, for each feature, there are some overlapped areas in the KDE plots between BC and BBC. Normally, the overlapped area represents the data range that is difficult to separate. However, due to the difference in central peak locations and the distribution, the overlapped areas are not large, especially for dissimilarity, correlation, and contrast. This indicates that these three are the most important features for the classification of BC and BBC images. At the same time, it can be found from the KDE plots and the scatter plot that two groups of data can be easily separated when these three features are involved. However, dissimilarity and contrast show a correlation coefficient of 0.99, indicating that they are highly correlated, and it is reasonable to keep only one. As regards to other features, taking energy and homogeneity as examples, the plots show that the BC features are completely covered by the BBC features. However, the BC features have narrower distributions than the BBC, and the data outside the BC data range can be classified as BBC. For example, when the homogeneity value is larger than 0.1 or the energy value is larger than 0.02, the image can be easily classified as BBC.

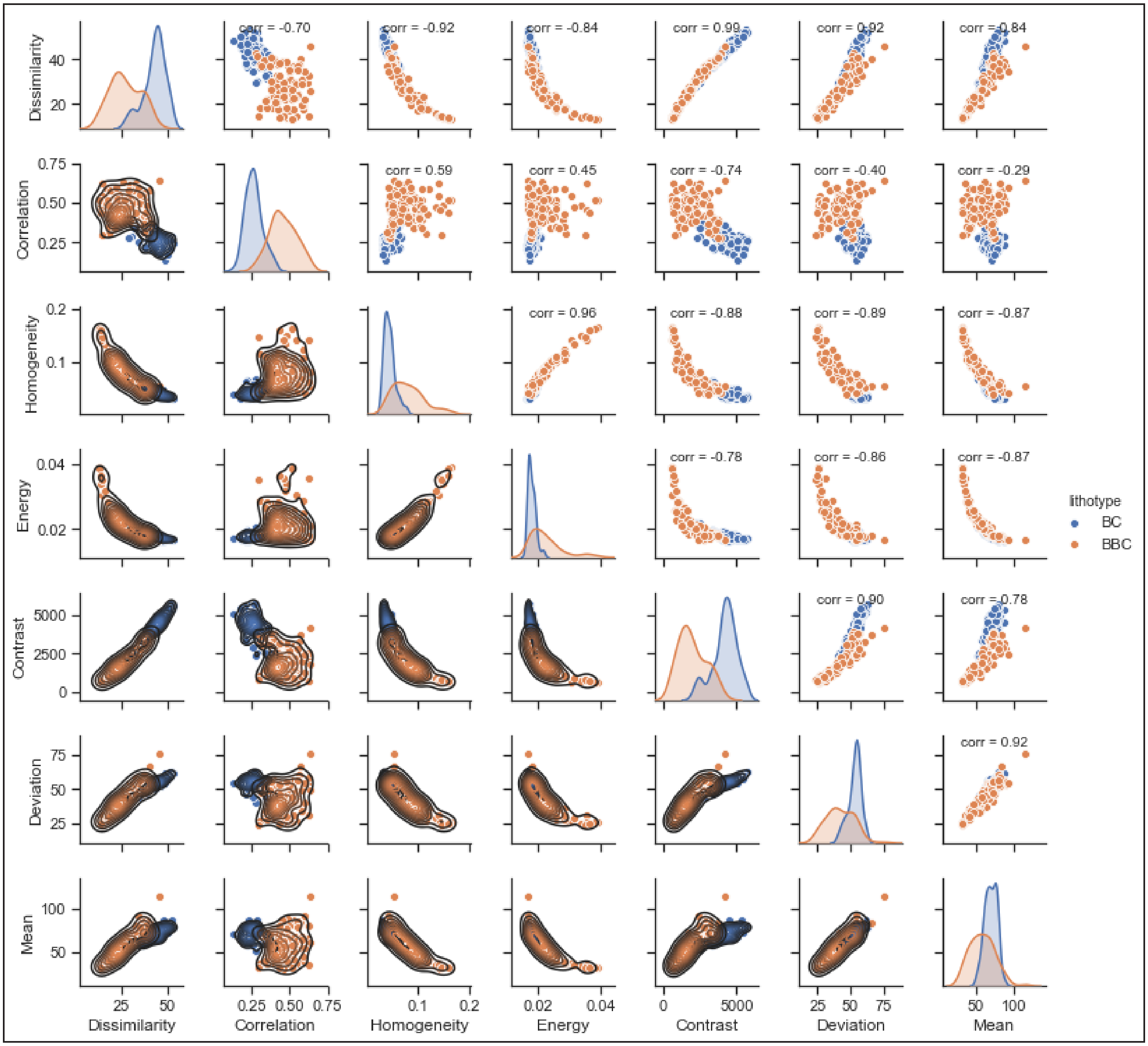


Figure 6. Pairplot of the GLCM features

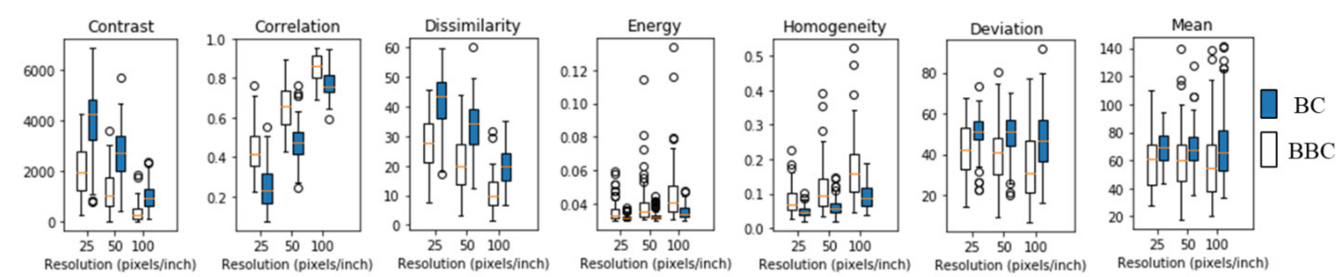
In summary, the pairplot shows that each feature can be used to separate some of the data, and among all these features, correlation, and contrast (dissimilarity) are the most important. When all of these features are combined for the classification, a good performance can be expected.

Influence of Resolution on Coal Lithotype Classification

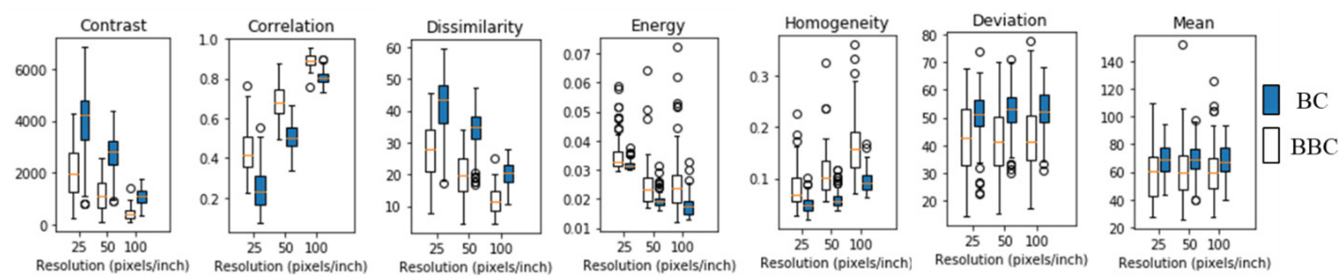
The GLCM is a texture analysis method that depends on the spatial relationships between pixel values in the image. When the coal images of different resolutions are used, the spatial relationships between pixel values change and different GLCM features can be obtained. The resolution of an image refers to the amount of detail it contains, typically measured in pixels per unit area (e.g., pixels per inch or pixels per centimeter). In order to understand how the image resolution can affect the GLCM features and the lithotype classification, the change of image features with varying resolution is investigated in this section. The change of image resolution was achieved by resizing the images, which allows the change of image dimensions (width and height) to achieve a different scale or resolutions. It is important to note that resizing an image is not a perfect substitute for capturing an image from different distances, as resizing only changes the dimensions of the image and does not capture the same level of detail that would be present in the original scene. It can mimic the visual appearance to some extent, but it might not fully replicate the effects of perspective, focus, and depth that result from changing the physical distance between the camera and the subject. However, it is a helpful tool to study the visual impact of distance changes.

Various resolutions, namely 1, 2, and 4 pixels/mm (25, 50 and 100 pixels/in) were used in this study. The resolution of 1 pixel/mm was the recommended minimum resolution in the previous study (Yu et al. 1997)methods for its characterisation and analysis are poorly developed. Banding texture was obtained manually from the coal face and core at a minimum resolution of 1 mm. Window filtering was used to determine the optimum resolution (30–50 mm, and the other two resolutions were higher than the recommended minimum value. In addition, when the GLCM parameters are compared with different resolutions, there are two ways to make the comparison. The first one is based on the patch size with the same pixel numbers, and different covered areas can be obtained because of the different resolutions. For this method, a patch size of 50×50 pixels was used for the analyses, leading to patch sizes of 50×50 mm, 25×25 mm, and 12.5×12.5 mm, respectively. The second method is based on the patch size with the same covered areas, and different pixel numbers are required when the resolution varies. For this method, a patch size of 25×25 mm was used for the analyses, resulting in patch sizes of 25×25 pixels, 50×50 pixels, and 100×100 pixels, respectively. The calculated image features with varying resolutions and two different comparison methods are shown in Figure 7.

For the first method, the covered area reduces with the increasing resolution. Although the increasing resolution helps to capture finer details, the decreasing area increases the randomness of the features, potentially leading to higher variation. These conflicting influences may show different effects on different features. Figure 7 (a) shows that the variation in contrast, correlation, and dissimilarity decreases with increasing resolution, while the variation in energy, homogeneity, deviation and mean becomes larger with the increase in resolution. For the second method, the same area is covered, and the higher resolution can capture finer details without losing the texture information at a coarser spatial scale. It helps to capture consistent image features. It can be found from Figure 7 (b) that there is a general trend of reducing variation with increasing resolution. The second method can provide better comparable results than the first one. Thus, it is recommended to use the second method for the comparison with different resolutions. The less variation with increasing resolution for the second approach indicates that the data are more concentrated. Since the features calculated for BC and BBC



(a) Box plot of various GLCM features of same patch size in pixel.



(b) Box plot of various GLCM features of same covered area.

Figure 7. Comparison of GLCM features with varying resolutions

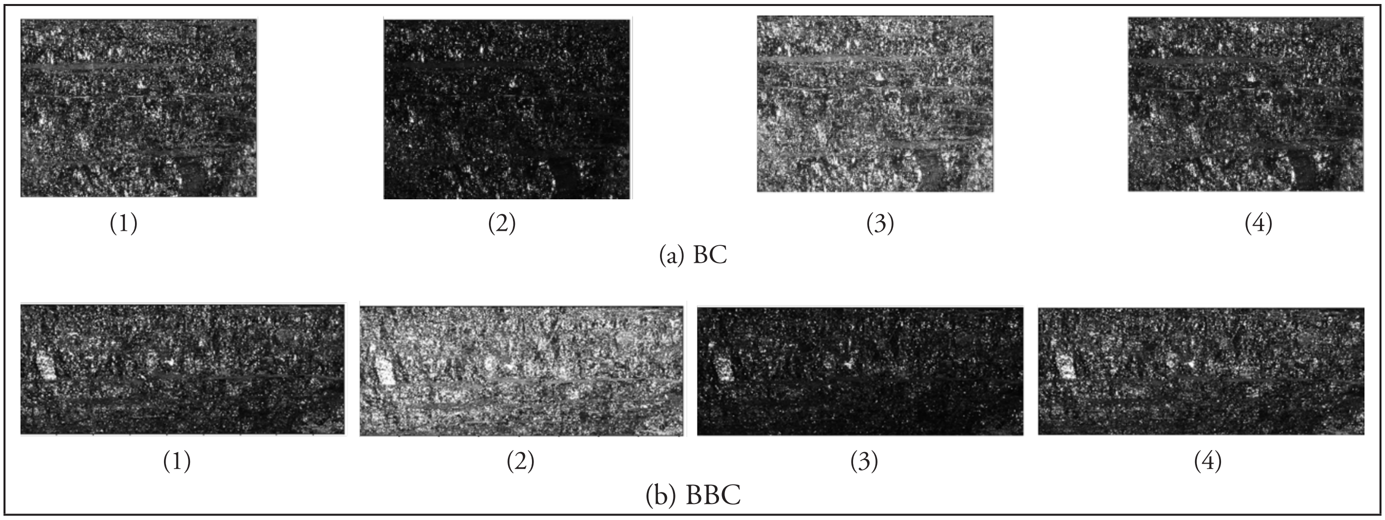


Figure 8. Coal images captured with different camera settings

are all concentrated, it can be expected from the KDE plot that there is less overlapped area, making it easier to classify these two groups of data. As a result, the increase in resolution can help capture the difference in textures between BC and BBC.

Influence of Camera Setting on Coal Lithotype Classification

The GLCM is a texture analysis method used to extract texture features from an image and the features are calculated from the co-occurrence matrix, which represents the spatial relationship of pixel intensities in an image. Different camera settings, such as shutter speed, F-stop, and ISO, can affect the GLCM features calculated from photos. These camera settings impact the way the images are captured, leading to changes in the pixel values, illumination, and texture characteristics (Slaker and Mohamed, 2016). The shutter speed determines the duration of light exposure on a camera's sensor, and longer shutter speeds capture more light, resulting in brighter images with reduced noise. Changes in shutter speed can affect pixel intensity distribution and impact GLCM features like contrast and homogeneity. The F-stop, also known as aperture, controls the amount of light entering the camera's sensor. Higher F-stop values (smaller aperture) reduce light, increase depth of field, and make the image sharper. F-stop changes can influence GLCM features related to image sharpness. The ISO value represents the sensitivity of the camera's sensor to light. Higher ISO values make the sensor more sensitive and result in brighter images but may introduce more noise. Changes in ISO can affect GLCM parameters related to image brightness and noise.

When taking photos for the fresh surfaces on the ribs, different camera settings were used to explore the influence of camera exposure on GLCM features. As recommended by Slaker and Mohamed (2016), a shutter speed between 1/60 s and 1/100 s, a F-stop value between 5 and 8, and an ISO value between 100 and 400 were selected, and different combinations of these settings were used when taking rib photos. Four examples were selected for each coal lithotype for the following analysis and are presented in Figure 8. Correspondingly, the image features calculated from the original photos without preprocessing are shown in Figure 9. The first images for BC and BBC are the ones that have been used in the analyses in previous sections. Compared to the first images, visual inspections show that the fourth image have similar luminance as the first ones while the second and third ones have higher or lower luminance than the first ones, resulted from different camera settings. Some common characteristics are observed between BC and BBC in Figure 9. The images with lower luminance have lower contrast, dissimilarity, deviation and mean values and higher energy and homogeneity values, while the images with higher luminance have higher mean value; but in general, the GLCM features vary with the exposure.

Instead of using the original photos captured with different camera settings, image preprocessing steps, namely normalization and histogram equalization, were taken to improve the quality of the images before applying texture analysis. These steps can help enhance the visibility of texture patterns and ensure that the image data is suitable for texture analysis. Image normalization was used to standardize the pixel values to a specific range, such as [0,1] or [0,255], to ensure that all images have consistent pixel

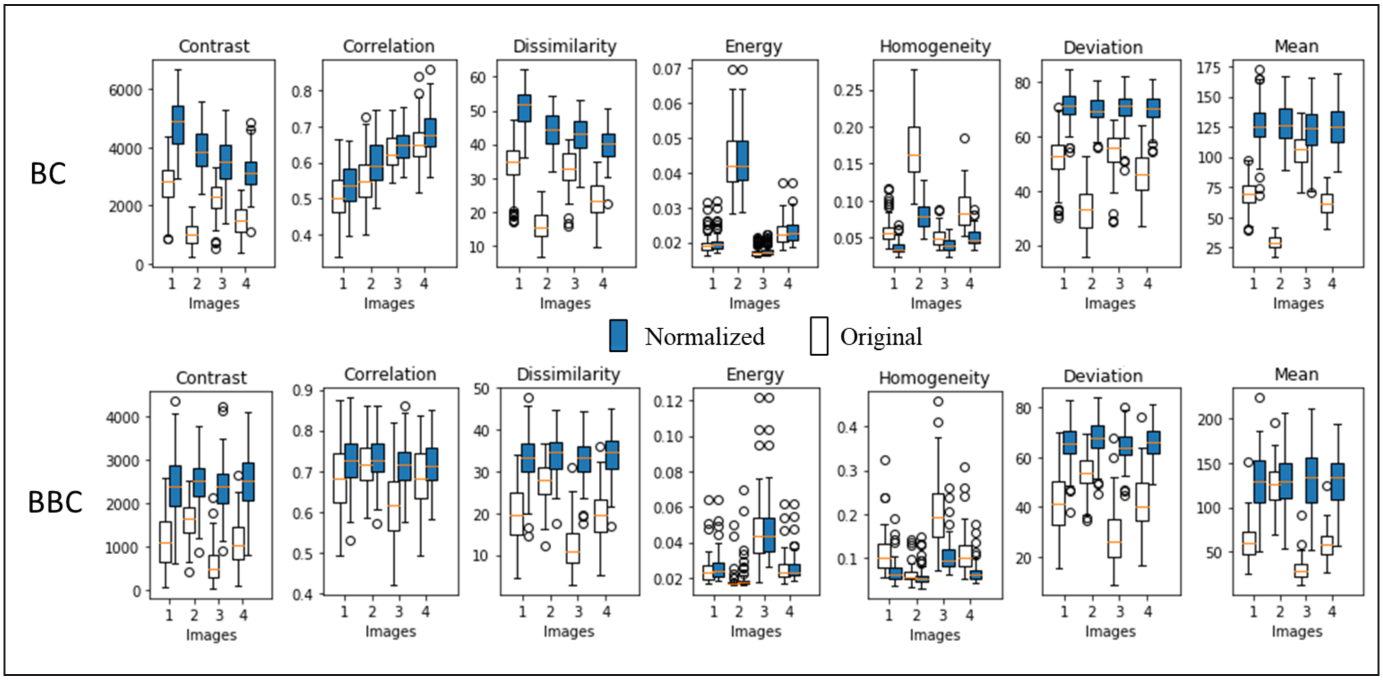


Figure 9. Box plots of various GLCM features with and without preprocessing

value ranges. It helps maintain data consistency across different images. In addition, histogram equalization was used to improve contrast and enhance the details in an image by redistributing the pixel intensity value in an image to cover a broader and more balanced range. It is particularly useful for enhancing the texture feature in images intended for GLCM analysis. Normalization and histogram equalization were combined to make texture patterns more distinguishable and consistent across different images, helping ensure that texture features are calculated accurately and reliably.

The features for the preprocessed coal images are also presented in Figure 9. It can be found by comparing the features with and without preprocessing that, except the negligible influence on energy value, the preprocessing step can significantly reduce the variation of the features. This makes the calculated features more consistent regardless of the camera settings. However, the comparison of the features between BC and BBC shows that the preprocessing step makes each calculated feature, such as deviation and mean, show similar distribution with close median values. This makes the features difficult to classify. The features still show differences after preprocessing for correlation and contrast (dissimilarity). Although the preprocessing step makes the calculated features closer, there are still differences for correlation and contrast (dissimilarity), making them still the most important features for the classification of BC and BBC.

SUMMARY AND CONCLUSIONS

The results from this study show that the coal images of different lithotypes have different textures and the difference in image texture can be quantified with GLCM method. Although the GLCM features can be affected by the resolution and camera settings, they can be used effectively to classify the coal lithotypes. It demonstrates the potential of coal lithotype classification with rib photos, reducing the impact of human influence and easing the data collection process for rib stability analysis.

GLCM method was used to analyze the texture of BC and BBC images. Based on the recommended minimum resolution of 1 pixel/mm in a previous study, the GLCM parameters, namely direction (angle), distance and patch size, were optimized based on the BC and BBC images. An angle value of 0 degree, a distance value of 1, and a patch size of 50×50 mm were used first for the analyses. The box plots of the GLCM features show that the texture of BC has higher contrast and dissimilarity levels on average, indicating that the image texture of BC has significantly local variation in pixel intensities, resulting in sharp transitions. At the same time, the textures of BC show generally lower correlation, energy, and homogeneity levels than those of BBC, indicating that BC images have more random, diverse, and heterogeneous textures. In addition, the GLCM features for BC, in general, have a smaller spread of values, indicating that the GLCM features for BC are tightly clustered and the textures tend to be more consistent than that of BBC.

In addition, the influence of resolution on the calculated GLCM features was investigated. The resolution can affect the level of details that an image can capture and thus vary the image textures. The results show that if the image features are extracted from the patches of the same size (area), the increase in resolution can help capture finer details without losing the global texture information. It helps to capture consistent image features with less variation, leading to the narrower distribution of the features. Thus, the increase in resolution can help capture the difference in texture between different coal lithotypes.

Finally, the influence of camera settings on the image features was studied. Different settings with shutter speed, F-stop, and ISO were combined to take rib photos and varying exposures can be observed in the photos through visual inspection. The calculated image features show variation with the exposure. The images with lower luminance have lower contrast, dissimilarity, deviation, and mean values and higher energy and homogeneity values, while the images with higher luminance have higher mean value. The image preprocessing step with normalization and histogram equalization can effectively reduce the variations resulted from camera settings. However, it increases the difficulty for lithotype classification.

LIMITATIONS

The work completed in this study was from an exploratory research perspective to evaluate the effectiveness of using GLCM method to classify coal lithotypes of photos previously taken by NIOSH researchers at field sites. The findings are limited to the specific lithologies analyzed during the study from the photos available for a proof-of-concept evaluation and limited to the camera (Nikon D550) and shutter speed, F-stop, ISO, and other default settings used. The application of the proposed method would need to be validated for other cameras, settings, mine sites, and mine conditions for broader concluding remarks on the effectiveness of using this technique for automated lithological detection.

DISCLAIMER

The findings and conclusions in this study are those of the authors and do not necessarily represent the official position of the National Institute for Occupational Safety and Health (NIOSH), Centers for Disease Control and Prevention (CDC). Mention of any company or product does not constitute endorsement by NIOSH.

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