Identification of Biomass Powder Fuel Based on Image Processing and Feature Engineering

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Abstract. Biomass fuels have a wide application prospect in thermal power generation. Different fuels have different physical and chemical properties and are reflected in the complex combustion and pollution emission properties during application. It is necessary to determine the type of biomass fuel. This paper proposes an image-based method to identify the type of biomass fuel and some related work derived from it. A feature selection rule that can explain the physical meaning of the fuel was designed. Through an ensemble learning method named Stacking and an image partition recognition strategy, the recognition task is integrated from the perspective of algorithms and data. The 10-fold cross-check on the training set has an accuracy of more than 98%, and the effectiveness of the image partition recognition strategy was proved mathematically.

1. Introduction

The widespread use of fossil fuels is likely to cause excessive emissions of greenhouse gases such as CO₂. Additionally, the NOx and particulate matter produced during the combustion process is likely to have a negative impact on air quality. Besides, fossil fuels are facing a crisis of limited reserves. The application of biomass fuels, especially co-firing with coal is thus an effective solution. Biomass has the characteristics of low calorific value, variable chemical composition, special physical structure, and high investment costs. Its raw material supply process has certain dangers, which limit its wide application [1]. Therefore, it is common to mix the biomass fuels with coal and transform coal-fired power plants into co-fired power plants to save costs. Co-firing of biomass and coal can effectively reduce pollution emissions, and can also effectively alleviate slagging, fouling, ash accumulation, and other phenomena [2]. It can also effectively reduce greenhouse gas emissions. Hence, the co-firing solution has significant economic feasibility [3].

Before biomass fuel is used, it needs to go through pretreatment, grinding, granulation, and other steps. The fuel particles may need to be broken again before burning. Therefore, solid biomass fuel often needs to be turned into a powder state during use [4]. Different biomass fuels have different physical and chemical properties. Shan et al. [5] put forward that different biomass particles have different combustion characteristics. A study by Hupa et al. [6] found that different biomass fuels have different special compositions with different chemical properties. Luo et al. [7] studied the different mixing ratios of biomass co-firing and found that different mixing ratios affected the overall combustion behavior. Schiemann et al. [8] pointed out that the shape and size of biomass particles also have a certain impact on the combustion characteristics. The study by Panahi et al. [9] shows that the particle size of biomass has an impact on the combustion characteristics of co-firing. The process of crushing biomass requires a certain economic cost, and for coal of a specific size, there is the most
economical particle size range. The series of studies referenced above point out a common direction, which is the needs for effective identification of the types, prediction of the composition and accurate detection of the features of biomass fuels. This can predict the physical and chemical characteristics, combustion characteristics, and pollution emissions of the fuel, so that effective control and decision-making can be carried out on the combustion process. And it can solve the problem of fuel quality assessment, and help determine whether the composition is qualified and whether there is adulteration or not.

Image processing techniques has unique advantages for some detection tasks in the field of thermal power generation due to its simple principle, as it is relatively time-saving, and does not require too much investment in equipment. Through the detection of corresponding objects, prediction, identification, and optimization tasks can be completed. For example, Li et al. [10] reached the effective prediction of NOx emissions through flame radical imaging and deep learning. Zhang et al. [11] accomplished the prediction of ash content through the collection and recognition of coal images on a moving conveyor belt. The research of Zhou et al. [12] completed the identification of mixed coal. Li et al. [13] successfully carried out characteristic engineering research on flame radical spectra to realize the identification of biomass fuel. Hobson et al. [14] realized the detection of texture features in coal and gangue images and achieved the distinction of coal and gangue. Li et al. [15] also pointed out the direction for improving combustion efficiency and reducing the pollutants. Additionally, the problems solved using the image processing technology in thermal power plants include dynamic and static problems. Dynamic problems include monitoring of single-particle combustion [5,16,17], detection of flame images [12,18], extraction of flame radicals [10,13], and detection of solid fuel on conveyor belts [11]. Static problems can provide a theoretical basis for solving dynamic problems. Lu et al. [19] completed the detection of morphological characteristics of biomass particles with different diameters. Wang et al. [20] achieved particle size distribution measurement through a static imaging system, which indicated the feasibility for subsequent online measurement.

The identification of fuel and the prediction on mass fraction of powder mixture are of great significance to the boiler safety, economy, and effective combustion. Traditional fuel identification methods often use methods such as burning, chemistry, radiation, etc., to obtain accurate fuel type information, and to detect its moisture, ash, calorific value, and volatile content for fuel quality analysis. These methods are mostly offline. This technology is cumbersome, time-consuming, and the cost of the equipment used is also high [13]. The image processing method solves the above limitations and has the advantages of non-invasiveness, rapidity, the possibility of online measurement, and high accuracy. Similar to reports in the literature, it is therefore feasible to carry out fuel identification through an image processing technology [5,12,13,15]. The existing research is often carried out on flame images, and thus, there is still room for research on biomass fuel identification.

Based on an image processing methods, our research proposes a measurement method with simple principles, low equipment requirements, short time-consumption, non-invasiveness, and no damage to raw materials. Feature extraction and combination were performed on the biomass particle images obtained using the flatbed scanner. Based on retaining the physical meaning reflected by the features, through a simpler integrated learning algorithm, the effective identification of the types of biomass fuel was achieved. This lays a foundation for the subsequent realization of online continuous measurement. Additionally, we also completed the prediction of the mass fraction of each component in the mixed particles through different methods, and proved its effectiveness and applicability.

2. Equipments and Samples

2.1. Equipments
In the image acquisition system, the commonly used image acquisition tools are the CCD camera, SEM, flatbed scanner, etc. It is necessary to ensure uniform lighting conditions and stable exposure time for static image acquisition and the corresponding analysis tasks to control variables. In this
scenario, considering the experimental conditions, cost, accuracy, and other factors, a flatbed scanner with a matrix CCD image sensor was considered as a suitable choice.

Figure 1. Image acquisition system and a possible industrial application scenario of the study.

As Figure 1 shows, the image acquisition system refers to the solution of Zhang et al[21]. In this study, a white opaque hood with a thickness of 5 cm was used with the scanner in order to provide stable and uniform light. The scanner was HP-G4010 and the imaging parameters were set at 4800dpi (4800 pixels stand for 1 inch, or 2.54cm). The image saving format was BMP. Adaptive lighting was not used, but automatic sharpening was turned on. Under these parameters, the scale factor of the captured image was 5.3μm, which means that each pixel represents a 5.3μm*5.3μm square in the real world. Due to memory limitations, an area of about 8cm*8cm size at most can be collected at one time, containing information of about 220 million pixels.

2.2. Samples
In this study, six biomass powder fuels, namely willow, corn cob, rice husk, wheat straw, rice straw, and corn stalk were involved, and numbered the fuels from B1 to B6.

The biomass fuel needs a series of pre-processing work before using the scanner to collect images. Considering that biomass particles have the most economical particle size range when in apply, the biomass particles can be sieved according to their particle size distribution defined by the mesh size. It is appropriate to select the particle size distribution range of about 100 μm. According to the actual situation, sieves with mesh sizes of 150 μm, 200 μm, 300 μm, and 400 μm are recommended for screening the fuel. Finally, we extracted fuel in the range of 200-300 μm or 300-400 μm, depending on the type of fuel.

The screening work can effectively remove impurities that are too large or too small in size. In the experimentation, vibration sieving was applied to screen the fuel by adjusting the shock intensity to 100 for 10 min. After screening of each fuel, an ultrasonic cleaner was used to clean the screen.

2.3. Image Processing
It is necessary to perform filtering, grayscale transformation, edge detection, binarization, and connected domain detection for the original image. The purpose of this series of work was to effectively segment the fuel particles and prepare for the extraction of morphological features.

Prior to this, the foreground could be filtered first with the background set to black pixels. The purpose of doing this was to simplify the subsequent complicated calculations. And the difference from binarization was that this step only processed the background pixels. The background color of each area inside the scanner may be different during the scanning process. To minimize the influence of irrelevant factors as much as possible, it was also necessary to unify the background.
As shown in Figure 2, the foreground extraction can reach the effect as follows. After foreground extraction work, an accuracy rate improvement of 3%-5% has been achieved. Moreover, setting the background pixels to black in the foreground extraction work can effectively highlight the part of the particles to be measured in the image. In other words, this improved the contrast of the entire image, which is conducive to the segmentation of adhered particles. It provides great convenience when using the watershed algorithm for automatic segmentation or using software such as labelme for manual labeling.

![Figure 2. Foreground extraction.](image)

In addition, in order to achieve the extraction of morphological features to complete tasks such as single particle recognition, we have also done some work on particle segmentation.

3. Identification of the biomass

3.1. Feature extraction and selection

Most research teams use one or two of color features, texture features, and morphological features to complete image recognition, which is often effective in solving classification problems. For this research, using some color features or combining color features with texture features can achieve well classification results. Therefore, the main function of the morphological features is to reflect the physical properties of the fuel particle size distribution, and the features have a certain value for the identification work, especially the identification of single particles.

This research involves 42 color features, 119 texture features and 8 morphological features.

3.1.1. Color features

RGB color space and HSV color space are two commonly used color spaces in image processing tasks. The RGB color space is designed based on the principle of color light emission, and the HSV color space is relatively intuitive and conforms to human perception of color. By converting the RGB color space to grayscale by the following formula, the amount of calculation can be reduced, and to a certain extent reflect the overall color space information of the image.

$$Grey = 0.299 * R + 0.587 * G + 0.114 * B$$

3.1.2. Texture features

The gray-level co-occurrence matrix (GLCM) can be used to extract the texture features [22]. It reflects the relationship between each pixel and its surrounding pixels. Like the principle of the GLCM, Hong [23] proposed the gray-level gradient co-occurrence matrix (GLGCM) to extract texture features. That is, add the gradient information of the image to the GLCM, so that the matrix can contain more texture information. For a total of 7 components in different color spaces, with the GLGCM matrix, the corresponding 17 texture features are extracted, totaling 119.

3.1.3. Morphological features

Morphological features are also widely used in image recognition of particulate matter. Lu et al. [19] mainly used aspect ratios to characterize the particle size distribution of wheat straw particles in different particle sizes. Cardona et al. [24] worked on the morphological features of particles with
different sizes and shapes and put forward an effective processing framework. Bai et al. [16] studied the combustion behavior of a single pulverized coal particle based on high-speed imaging and image processing methods, and pointed out that the particle size, an important morphological feature, has a significant impact on the combustion behavior. Generally, the calculation of the morphological features of the particles requires the extraction of the edge, the circumscribed rectangle or circle, and the convex hull.

3.2. Feature selection

For classification work, it is necessary to look for features with the smallest gap in a certain class but the largest gap between classes. In order to retain the original meaning of the features, we do not use PCA and other similar methods to reduce the data dimension, but filter features through some specific criteria. The coefficient of variation is an optional parameter, which is defined by Eq. 2, and will be directly referred to as CV below. In the formula, \( \mu \) stands for the mean value of a feature in a certain type of biomass fuel image, \( \sigma \) represents the standard deviation.

\[
C_V = \frac{\sigma}{\mu}
\]

Among the remaining effective features, select the feature that distinguishes between classes as obvious as possible, and focus on the fuels that are difficult to distinguish. Taking into account the running time and the recognition effect, select 20% of the effective features. For each type of feature, \( d_y \) is the degree of discrimination between the i-th fuel and the j-th fuel, and \( \text{diff}_i \) is the total discrimination of the i-th fuel compared to other types (the sum of the degree of discrimination between classes), and several types of indicators are the bigger the better.

\[
d_y = |\mu_i - \mu_j|
\]

\[
\text{diff}_i = \sum_{j \neq i} d_y
\]

3.3. Fuel identification

Before the fuel recognition, it is necessary to standardize the data for the extracted features. Data normalization can make existing data better for identification work, and reducing the amount of calculation in machine learning.

Min-max normalization, zero-mean normalization and non-linear normalization are commonly used, like Eq. 5-7 showed. \( x \) is the value to be normalized, \( x_1, x_2, x_3 \) are the results after normalization, and \( X \) is a vector including all \( x \) from the images. \( \mu \) stands for the average and \( \sigma \) stands for the standard deviation.

\[
x_1' = \frac{x - \min(X)}{\max(X) - \min(X)}
\]

\[
x_2' = \frac{x - \mu(X)}{\sigma(X)}
\]

\[
x_3' = \frac{2}{\pi} \arctan(x)
\]

Different algorithms adapt to different data normalization methods, and our research found that the min-max normalization method can make the algorithm generally have better performance after the optimization of the hyper-parameters.

We use support vector machines(SVM), random forests(RF), artificial neural networks(ANN), convolutional neural networks(CNN), and stacking-based ensemble algorithms to test the recognition effect.

We found that in the recognition work, if the parameters are not adjusted, the task cannot obtain good results. Taking SVM as an example, its prediction score is only about 0.86 under the default parameters. This effect still has a certain gap to the requirements of industrial applications. There are many methods to choose from for parameter optimization of machine learning algorithms. A simple
and effective method is grid search. The principle of grid search is to exhaust the predicted results of the parameter combinations to be searched, and select the best from them.

Stacking is a strategy that combines the strengths of various models. To some extent, it has a structure similar to a neural network, and each model acts as a "neuron". In our research, we integrated different algorithms such as SVM, RF and KNN with different principles to improve the stability of the model.

Image partition is an effective method to improve the recognition effect. Considering the particle size involved in this study, a 1792 side-length image already contains enough effective information. In practical applications, if a CCD camera is applied to continuously collect images of a specific area, the area size can be larger than the length of 1792 pixels with the 5.3\(\mu\)m\(^2\) pixel size. Therefore, we can re-cut the collected image into the size of 3584 side length and compare it with the corresponding four 1792 side regions to illustrate the effectiveness of image partitioning.

### 3.4. Comparison of results

#### 3.4.1. The results of machine learning

We compared the recognition effects of various algorithms on the feature set. The accuracy on validation set, time consuming and parameters after grid search are shown in the following table.

It should be noted that the effect listed in the table will vary according to factors such as the division of the training set, but the gap will not be too large. Among them, the stacking algorithm after tuning is not necessarily better than the SVM algorithm under different conditions, but when dealing with different data processing methods, the stacking method has good robustness.

For example, the accuracy of SVM drops to about 95% when using zero-mean normalization. However, the stacking method can still reach more than 96%, and the final result of the stacking strategy is often the one that converges to the best effect among the several algorithms participating in the integration. The confusion matrix of the stacking1 algorithm is shown in Figure 3.

Moreover, we also found in experiments that although the SVM algorithm performs well in most cases, it will fail to converge after tuning parameters in some recognition tasks. We can slightly sacrifice some accuracy and use the stacking2 method based on default parameters, which not only has a significant improvement in time, but also its recognition effect can meet industrial applications.

![Figure 3. The confusion matrix of Stacking1.](image)

| Algorithm | Parameters                                                                 | Time/s | Accuracy  |
|-----------|-----------------------------------------------------------------------------|--------|-----------|
| SVM       | kernel='poly', C=10000, degree=3, gamma=0.5, class_weight='balanced', coef0=0 | 8.14   | 98.14%    |
KNN
n_neighbors = 3,
weights = 'uniform'
0.94 95.72%
RF
max_features = 0.4, n_estimators = 300,
max_depth = 10
6.33 95.15%
ANN
alpha = 1e-5, learning_rate = 'adaptive',
hidden_layer_sizes = 60,
learning_rate_init = 0.1
4.46 97.78%
Stacking
1 Stacking SVM, KNN and RF with listed parameters
65.04 98.26%
Stacking
2 Stacking SVM, KNN and RF with default parameters
18.37 96.42%

CNN-based methods can also apply for image recognition, there is no need to carry out complex artificial feature design. Although its features are automatically extracted by the network, the features do not have actual physical meaning. Additionally, the space occupied by the parameters, the portability of the model, and the training of the network are all issues that need to be considered in the application.

We also designed a lightweight CNN structure with RNN module for this research to explore the feasibility of this solution to achieve online continuous recognition in practical applications. After 2000 steps of training, its accuracy and loss tend to be stable. We have found that when the training set is not very large, that is, when there is a certain over-fitting phenomenon, the accuracy can also exceed 92%.

We have also carried out identification work on four types of mixed particles. We selected images from groups with different mass fraction ratios. Its comprehensive accuracy is about 93.5%, which has certain practical application value.

3.4.2. Image partition
The image partition is an integration of data, in other words, it is a mathematical strategy that applies combinatorial theory, like the Eq. 8.

\[
C_n^m = \frac{m!}{n!(m-n)!}
\]  

In our research, the accuracy of the Stacking strategy is between 96.5% and 98.3%. We use the 4-partition method to re-cut the data set into 3584 side-length images, which contain four 1792 side-length regions. For 3584 side-length areas there are about 900 images.

If we use simple voting and think that when at least two areas in an image are misclassified, the image is marked as wrong label. In extreme cases, there are only 63 images are misclassified. However, this is practically impossible to happen. In fact, Using Eq. 9 can clearly calculate the expected error based on the 4-partition method, and it can be simplified to Eq. 10.

\[
E = C_4^2 \cdot p^2 (1 - p)^2 + C_4^1 \cdot p (1 - p)^3 + (1 - p)^4
\]

\[
E = (1 - p)^2 (3p^2 + 2p + 1)
\]

The expected error of the 4-partition recognition and the accuracy of the algorithm have a relationship as shown in Figure 4.

![Figure 4. The relationship of the expected error rate and the accuracy of the algorithm.](image-url)
Indeed, using the image partition strategy, the accuracy can reach more than 99%. The partition strategy can also locate possible abnormal areas in the image. And we can also use different image recognition algorithms for secondary verification, such as CNN-based methods.

Figure 5. Application scenarios of partition recognition.

Like Figure 5 shows, case 1 represents that one of the areas is classified incorrectly. The algorithm of other principles can be used for the second verification. If the result of the second verification is correct, the entire image is marked as the correct label, but relevant information needs to be uploaded. If the result of the second verification is still wrong, mark this area as a suspicious area and submit it to engineering personnel for manual verification and processing. Case 2 represents that two or more areas in the image are divided incorrectly. At this time, the specific information of the incorrectly divided image is directly uploaded to the engineering staff for manual determine and deal with it accordingly.

4. Conclusion
Through the image processing, feature engineering, and ensemble strategy on data and algorithm, we have completed the effective identification of the biomass fuel image collected by the scanner. According to the characteristics of different image acquisition systems, this technical route can be put into use with slight adaptations. Our research mainly achieved the following results:

• Through a series of image processing work, especially the foreground extraction step, the effective area in the image is highlighted.
• Designed an effective feature selection strategy.
• Designed an effective data and algorithm integration strategy to realize the effective identification of biomass fuel, and has good repeatability.
• In order to realize the online fuel type identification, the feasibility was verified, and a complete technical route was designed.

In the future, we are working on realizing online continuous identification of biomass fuel through this research. And we will add more fuel groups and use pulverized coal for experiments. And we are working on the mass fraction prediction task as well.

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