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Combining flame monitoring techniques and support vector machine for the online identification of coal blends

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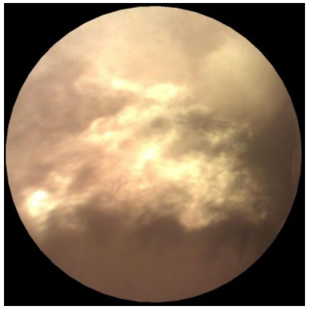
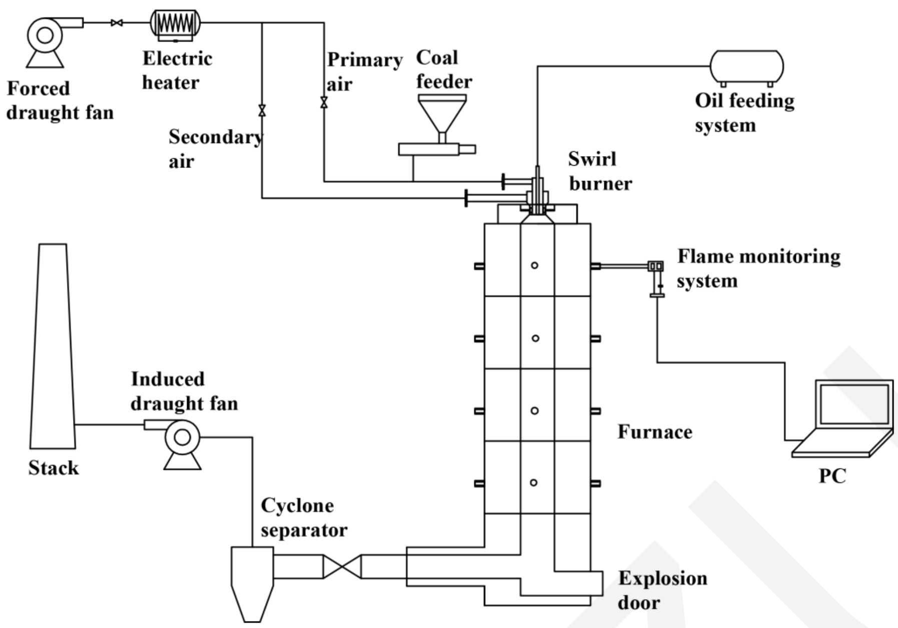
Paper content overview

- Coal blends have been regarded as an attractive fuel in coal-fired power plants to minimize fuel costs, improve fuel flexibility and reduce pollutant emissions.
- Coal blends identification in coal-fired power plants will enhance boiler safety, improve combustion efficiency and reduce pollutant emissions.
- With the development of diagnostic methods, significant research has been devoted to monitoring coal combustion. Flame monitoring techniques have generally been applied to extract flame features.
- Machine learning algorithms are applied to identify coal types using the flame features extracted by flame monitoring techniques.
- In this paper, the method of ReliefF was used to evaluate the importance factors of all extracted flame features quantitatively. SVM was applied to identify coal blend types under variable conditions, in a 300 kW coal-fired furnace.

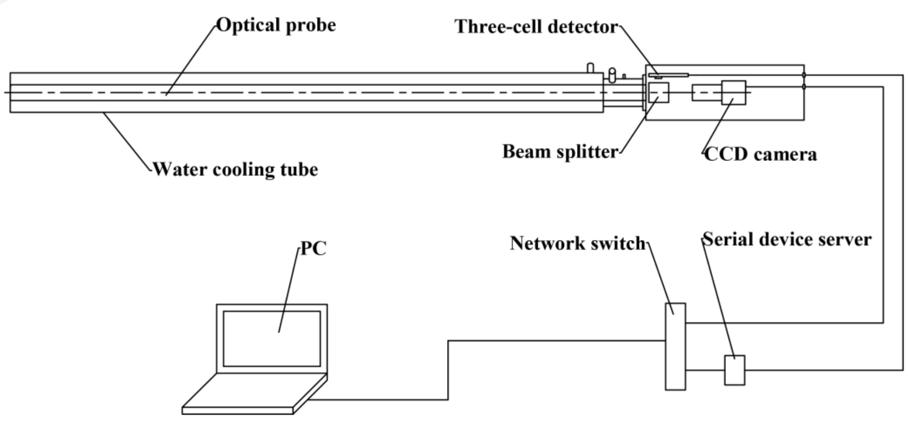


Experimental facility



- The 300 kW coal-fired test facility contains a vertical furnace, a coal feeder, and a swirling burner.
- The total height of the furnace is 3.95 m, and its internal diameter is 0.35 m.
- The flame monitoring system was mounted in the furnace at a distance of 0.244 m from the swirling burner outlet.

- The flame monitoring system consists of a 90° angle lens inside a water-cooling tube, a beam splitter, a three-cell detector, a camera, a serial device server, a network switch, and a PC.
- With the introduced serial device and network switch, the signal transmission of the improved system is stable.



Operating conditions

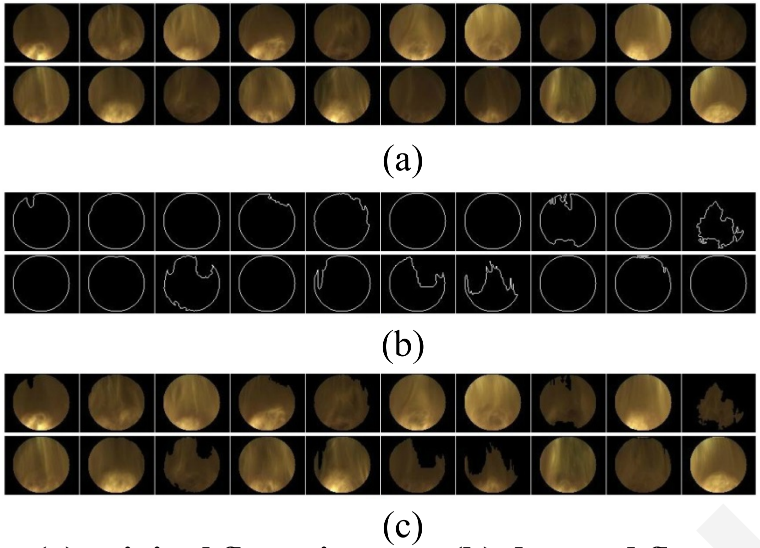
- Two single coals (A and B) and three coal blends (3A1B, AB, and 1A3B) were used to investigate the identification of coal blends.
- Coals 3A1B, AB, and 1A3B were composed of coal A and coal B with mass mixing ratios of 75%:25%, 50%:50%, and 25%:75%, respectively.

Sample	A	3A1B	AB	1A3B	B
Proximate analysis (wt%, ar)					
M	10.69	10.09	9.49	8.9	6.95
V	28.94	27.88	26.82	25.75	29.46
F	46.92	45.70	44.47	43.25	47.35
A	13.45	16.33	19.22	22.10	16.24
Ultimate analysis (wt%, ar)					
C	62.22	60.07	57.92	55.77	62.5
H	4.11	3.99	3.87	3.76	4.11
O	7.80	7.85	7.89	7.94	8.05
N	0.92	0.90	0.88	0.85	0.99
S	0.81	0.77	0.73	0.68	0.64
$Q_{ar,net}$ (MJ/kg)	23.92	23.12	22.32	21.52	23.88

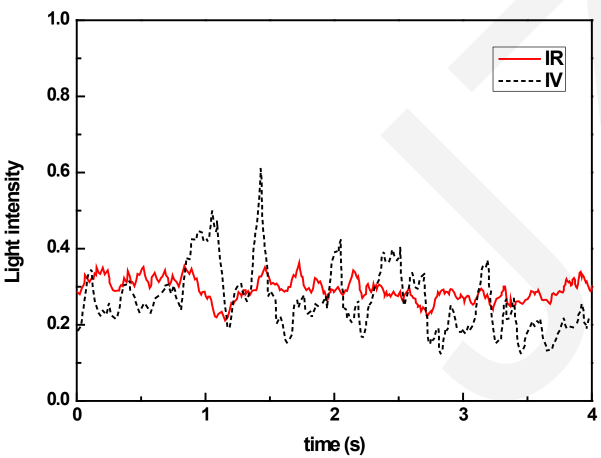
Case	Coal feed rate (kg/h)	Total air flow rate (kg/h)	PA/SA ratio
1	25	210.4	0.339
2	25	227.6	0.340
3	25	245.8	0.340
4	25	210.6	0.380
5	25	227.5	0.380
6	25	245.9	0.381
7	30	252.7	0.340
8	30	273.0	0.341
9	30	294.9	0.340
10	30	252.8	0.380
11	30	273.2	0.381
12	30	295.0	0.380

- The operating conditions, including variations in coal feed rate, total air flow rate and PA/SA ratio
- Each coal type was tested in 12 test cases.

Data acquisition & feature extraction



(a) original flame images; (b) detected flame edges; (c) defined flame zones



Typical light intensity signals

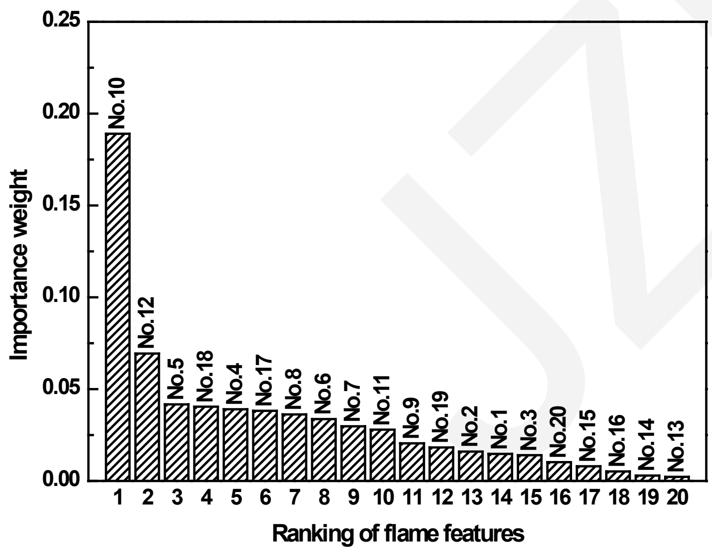
- Spatial flame features were extracted from flame images.
- Temporal flame features were extracted from light intensity signals
- Twenty flame features was extracted, including spatial and temporal flame features.

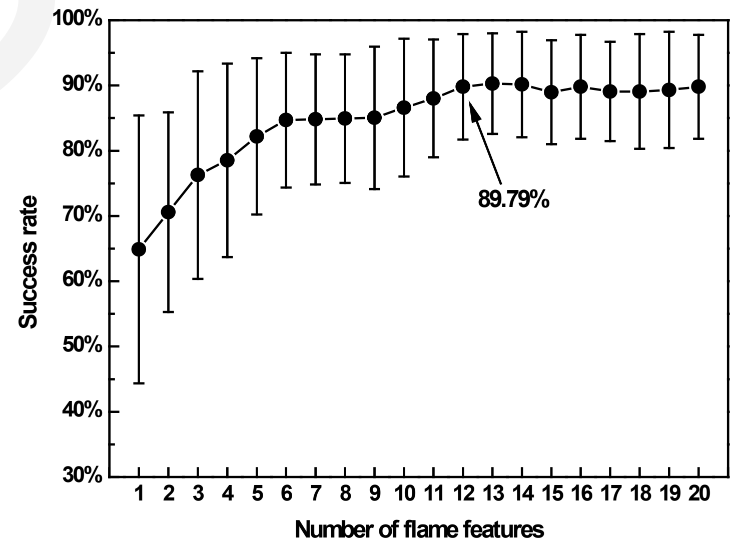
No.	Spatial flame features	No.	Temporal flame features
1	$P_{mean,R}$	9	$S_{mean,VI}$
2	$P_{mean,G}$	10	$S_{mean,IR}$
3	$P_{mean,B}$	11	$S_{std,VI}$
4	$P_{mean,R/G}$	12	$S_{std,IR}$
5	$P_{std,R}$	13	$S_{ske,VI}$
6	$P_{std,G}$	14	$S_{ske,IR}$
7	$P_{std,B}$	15	$S_{kur,VI}$
8	$P_{std,R/G}$	16	$S_{kur,IR}$
		17	$S_{flu,VI}$
		18	$S_{flu,IR}$
		19	$S_{f,VI}$
		20	$S_{f,IR}$

The optimal feature vector

- The rankings and the importance weights of the 20 flame features were evaluated by the method of ReliefF quantitatively.
- $S_{\mathrm{mean,IR}}$ is the most influential feature in coal type identification. The first 18 flame features explain 99.73% of the information of the datasets.
- Considering the overall precision, efficiency and stability, the first 12 of the ranked flame features were selected to identify the coal types.
- The selected flame features were Nos. 10, 12, 5, 18, 4, 17, 8, 6, 7, 11, 9 and 19.

$$R_{\mathrm{success}} = \frac{N_{\mathrm{success}}}{N_{\mathrm{total}}} \quad \text{......................}(1)$$





Effects of similarity on identification

- The combustion behavior of a coal blend is more similar to that of its component coal of higher volatile matter in the blend. Moreover, the similarity between a coal blend and its component coal increased as the proportion of the component coal increased
- One coal type can be mis-identified as another due to their similar combustion behavior:
  - A single coal may be mis-identified as a coal blend;
  - A coal blend may be mis-identified as another coal blend or a single coal.

Weighted average similarity coefficients

Coal α	Coal β					Mean
	A	3A1B	AB	1A3B	B	
A	-	0.6873	0.4518	0.4003	0.3751	0.4786
3A1B	0.6873	-	0.6332	0.4638	0.3904	0.5437
AB	0.4518	0.6332	-	0.6114	0.3613	0.5144
1A3B	0.4003	0.4638	0.6114	-	0.5437	0.5048
B	0.3751	0.3904	0.3613	0.5437	-	0.4176

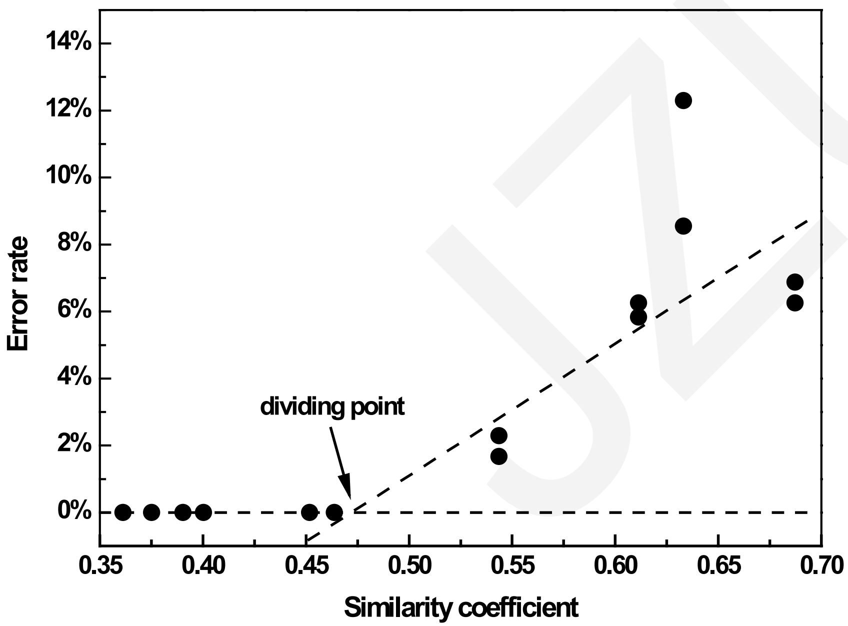
Number of correct and erroneous identifications

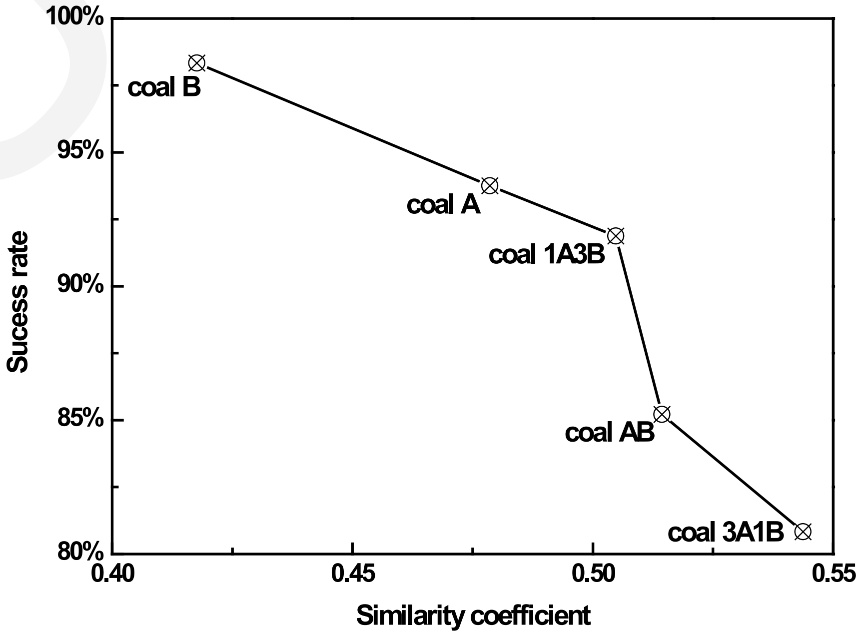
Target	Predicting result				
	A	3A1B	AB	1A3B	B
A	450	30	0	0	0
3A1B	33	388	59	0	0
AB	0	41	409	30	0
1A3B	0	0	28	441	11
B	0	0	0	8	472

Effects of similarity on identification

- The error rate was zero when the similarity coefficient was less than 0.4709. When the similarity coefficient was more than 0.4709, the error rate had a positive correlation with the similarity coefficient.
- A higher similarity coefficient resulted in a lower success rate. Because coal 3A1B had the highest mean similarity coefficient, it had the lowest success rate among the five coals. In contrast, coal B had the highest success rate, because it had the lowest mean similarity coefficient.

$$R_{\text{error},\,\alpha-\beta} = \frac{N_{\text{error},\,\alpha-\beta}}{N_{\text{total}}} \quad \text{............................(2)}$$





Conclusions

- Twenty flame features were extracted to investigate the combustion behavior of different coal types on a 300 kW combustion test facility.
- $S_{\mathrm{mean,IR}}$ was the most important of the 20 flame features, and played the dominant role in coal type identification.
- The number of flame features used to build an SVM model was reduced from 20 to 12 through combining the methods of ReliefF and SVM.
- A threshold value of 0.4709 was found for the relationship between the error rate and the similarity coefficient. The error rate remained at zero when the similarity coefficient was below the threshold. When the similarity coefficient was above the threshold, the error rate generally increased as the similarity coefficient increased.
- The success rate decreased as the similarity coefficient increased. A higher similarity coefficient resulted in a lower success rate.
- The present results demonstrate that the proposed system is effective for identifying coal blends with similar combustion behavior.

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