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Monitoring combustion process using image classification

***Abstract**. This paper presents comparison image classification method of co-firing biomass and pulverized coal. Defined two class of combustion: stable and unstable for three variants with different power value parameters and fixed amount biomass. Compared naïve Bayes classifier and support vector machine (SVM) with RBF kernel function. Experimental results show that achieved correct classification of images for the assumed variations.*

Streszczenie.** W pracy przedstawiono porównanie wybranych metod klasyfikacji obrazów dla współspalania pyłu węglowego i biomasy. Zdefiniowano dwie klasy spalania: stabilne i niestabilne dla trzech wariantów z różnymi parametrami mocy oraz stałą ilością biomasy. Porównano naiwny klasyfikator bayesowski oraz metodę wektorów nośnych z radialną funkcją jądrową (RBF). Wyniki badań pokazują, poprawną klasyfikację obrazów dla założonych wariantów. (**Monitorowanie procesu spalania w wykorzystaniem klasyfikacji obrazów).

Keywords: flame, combustion, active contour, image classification.
Słowa kluczowe: płomień, spalanie, klasyfikacja obrazów.

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Introduction

Combustion process is complex, nonlinear and non-stationary therefore analyzing is difficult. One method of diagnosis the combustion process is to use flame as the source of information. By analyzing the image of the flame can get information about the process almost without any delay. This is particularly important in the case of fuel combustion characterized by a high variability of physico-chemical properties. Current regulations require continuous increase in the proportion of biomass in order to obtain electricity. Co-firing of biomass and coal is the easiest way to use it but it is technologically difficult process due to the different characteristics of the components of the mixture combusted. Combustion tests were carried out on the test bench at the Institute of Energy. Measurements were made at the position of the camera perpendicular to the axis of the flame for different variants of power. After the initial analysis of images of the co-pulverized coal and biomass were determined sequence of images of stable and unstable combustion. Image classification method used to determine the state of the process. Article compared two methods for image classification with naive Bayesian classifier and support vector machine with RBF kernel function.

Classification using Naive Bayes classifier

The Naive Bayes classifier is simple effective and has low computational requirements. Let $\vec{i}$ be a input vector to classify and X be a defined class. In Bayes formula there are transform the probability $P(X \mid \vec{i})$:

(1) $$P(X \mid \vec{i}) = P(X)\frac{P(\vec{i} \mid X)}{P(\vec{i})}$$

P(X) can be determined from training data. Given a conditional independence of components of the vector $P(\vec{i} \mid X)$ is decomposed as follows,

(2) $$P(\vec{i} \mid X) = \prod_{j=1}^{D} P(i_j \mid X)$$

Where, i_j is the i^{th} element of $\vec{i}$. Equation presented above can be combined as follows:

(3) $$P(X \mid \vec{i}) = P(X)\frac{\prod_{j=1}^{D} P(i_j \mid X)}{P(\vec{i})}$$

From equation (3) $P(X \mid \vec{i})$ can be calculated and $\vec{i}$ can be classified with the highest $P(X \mid \vec{i})$.

A simple Bayes Classifier algorithm works as follows. Data sample can be represented by *n* dimensional feature vector. The can be m classes. Given an unknown data sample *S* the classifier will predict that *S* belongs to the class with the highest conditional probability on *S*. When classify sample *S*, for each class X_i equation $P(S \mid X_i)P(X_i)$ *is computed. Only if* $P(S \mid X_i)P(X_i) > P(S \mid X_j)P(X_j)$ *for* $1 \le j \le m$, *where j* is different from *i* [1,2].

Classification using Support Vector Machine (SVM)

SVM is generalized lineral (non-linear with RBF kernel) classifier and its characterized as classifier that can minimize the error. The main conception of SVM learning system is a separate hyper-plane by two parallel hyperplane. As shown in Fig. 1, the black dots and the white dots are the training dataset which belong to two classes. A vector is mapped to the intertval to establish a hyper-plane of the largest higher-dimensional space. The optical plane *H* is found by maximizing the margin value $2/\|w\|$. Hyperplanes H_1 and H_2 are the planes on the border of each class and also parallel to the optical hyperplane *H*. The data located on H_1 and H_2 are called support vectors This method can be effective, real-time to determine the brightness of the flame and to analyze the combustion state. For training data set $(x_1, y_1), \ldots, (x_l, y_l),\ y_i \in \{-1,1\}$, to find the optical hyperplane H, a nonlinear transform $Z = \Phi(x)$, is applied to x, to make x become linearly dividable. A weight *w* and offset *b* satisfying the following criteria will be found:

(4) $$\begin{cases} w^T z_i + b \ge 1, & y_i = 1 \\ w^T z_i + b \le -1, & y_i = -1 \end{cases}$$

Assume that the equation of the optical hyperplane *H* (Fig.1) is $w_0^T z + b_0 = 0$, then the distance of the data point in any of the two classes to the hyperplane is:

(5) $$\rho(w,b) = \min_{x|y=1} \frac{z^T w}{\|w\|} - \max_{x|y=-1} \frac{z^T w}{\|w\|}$$

A is to be found to maximize

(6) $$\rho(w_0, b_0) = 2 / \| w_0 \| = 2 / \sqrt{w_0^T w_0}$$

Then the search of the optimal plane *H* turns to a problem of a second order planning problem

(7) $$\min_{w,b} \Phi(w) = \frac{1}{2}(w^T w)$$

There are several kernels that can be used in Support Vector Machines models. These include linear, polynomial, radial basis function (RBF) and sigmoid function:

(8) $$K(x_i, x_j) = \begin{cases} x_i^T x_j & Linear \\ (\gamma x_i^T x_j + coefficient)^{degree} & Polynomial \\ \exp(-\gamma |x_i - x_j|^2) & RBF \\ \tanh(\gamma x_i^T x_j + coefficient) & Sigmoid \end{cases}$$

The most popular kernel types used in SVM is RBF [3,4,5,6,7].

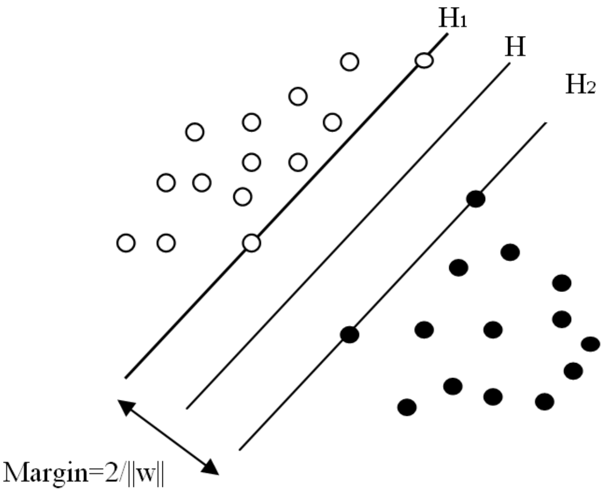

Fig.1. Binary classification using SVM

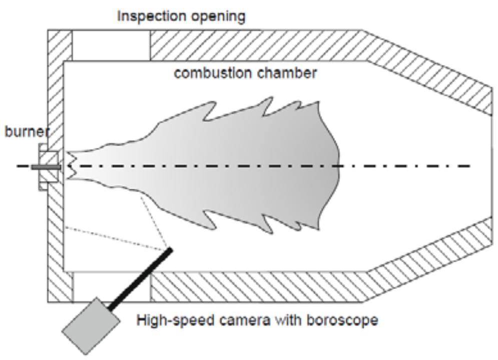

Fig. 2. Combustion chamber with camera mounting

Laboratory combustion facility

Combustion tests were done in a 0.5 MWth (megawatt of thermal) research facility, enabling scaled down (10:1) combustion conditions. The main part is a cylindrical combustion chamber of 0.7 m in diameter and 2.5 m long. A low-NOx swirl burner about 0.1 m in diameter is mounted horizontally at the front wall. The stand is equipped with all the necessary supply systems: primary and secondary air, coal, and oil. Pulverized coal for combustion is prepared in advance and dumped into the coal feeder bunker. Biomass in a form of straw is mixed with coal after passing through the combustion chamber has two lateral inspection openings on both sides, which enable image acquisition. A high-speed camera with CMOS area scan sensor was placed near burner's nozzle, as shown in Fig. 2. Flame images were transferred from the interior of the combustion chamber through a 0.7 m borescope. The camera was acquire 30 frames per second at its full resolution (1280x1024 pixels). The optical system was cooled with water jacket. Additionally, purging air was used to avoid dustiness of optical parts.[8].

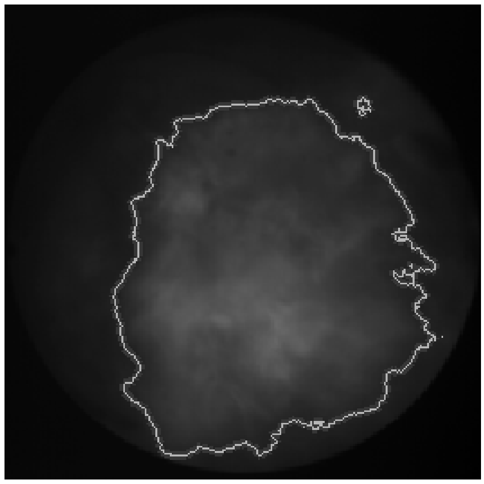
Fig.3. Stable combustion

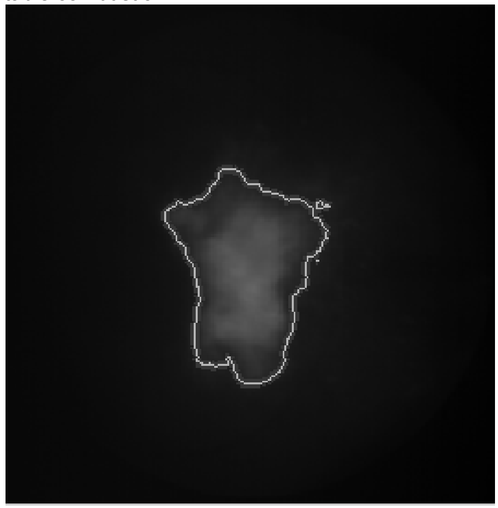
Fig.4. Unstable combustion

Combustion tests

Combustion testes were done for different variants (combinations) of the combustion facility, where thermal power (P_{th}) and excess air coefficient (λ) were set independently for known biomass content (20%), where λ is defined as quotient the mass of air to combust 1kg of fuel to mass of stoichiometric air. The exact values of thermal power and excess air coefficient are collected in Table 1

Table 1. The parameters of the variants

Variant	P_{th} (kW)	λ
1	250	0.75
2	250	0.65
3	250	0.85
4	300	0.75
5	300	0.65
6	300	0.85
7	400	0.75
8	400	0.65
9	400	0.85

The main goal of the tests are detected when co-firing is stable or unstable. Fig.3. present example of stable combustion with flame area contour and fig.4. present unstable combustion image sequence with flame area contour.

Results

In experiment were used first 10000 frame from all variants. Captured images were converted to 8-bit grayscale, thus pixel amplitude was ranging from 0 to 255.

In Table 2, three variants are tested in terms of stable combustion positive detection rates. It is defined as the number of correctly classified frames containing stable combustion divided by the total number of frames that contain stable combustion. There is compared Bayesian and SVM classifier.

Table 2. Comparison of positive detection stable combustion

Variant	Using Bayesian Classifier	Using SVM Classifier
1	80,7%	74,8%
2	81,4%	76,2%
3	79,8%	74,5%
4	77,3%	73,8%
5	76,8%	72,4%
6	76,2%	72,1%
7	72,4%	70,3%
8	74,3%	68,5%
9	76,4%	71,4%

In Table 3, three variants are tested in terms of unstable combustion positive detection rates. It is defined as the number of correctly classified frames containing unstable combustion divided by the total number of frames that contain stable combustion.

Table 3. Comparison of positive detection unstable combustion

Variant	Using Bayesian Classifier	Using SVM Classifier
1	72,2%	69,6%
2	73,4%	65,4%
3	75,8%	73,6%
4	73,1%	71,1%
5	69,1%	62,1%
6	74,8%	71,3%
7	70,6%	68,9%
8	68,7%	64,3%
9	72,4%	70.2%

Based on the above results, it is found that Bayesian classifier give better performance than implemented SVM classification tool.

Conclusions

In this paper we propose flame image features classification based on Naive Bayesian classifier and Suppoert Vector Machine classifier. The experiment results demonstrate that methods used are not sufficient to properly detect the state of the process. To correctly assess the state of the process is required detection above 90%

Future work will be concentrate to implement other classifier method and algorithm. The aim is to use the method, thats allows to monitor combustion process in real-time.

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