Intelligent Sensor for Thermal Process Control using Convolutional Neural Network

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Abstract. A thermal combustion process involves three variables: the fuel (which oxidizes and gives off heat), the comburent (which accelerates combustion), and the heat source. The proportion of these three variables determines the behavior of the process, and in the case of industrial production, their control is fundamental to guarantee continuity, quantity, and quality of the product. In the case of carbonization of plant material, the control of oxygen is decisive to guarantee these production parameters. However, the measurement in real-time becomes a complex problem due to the process temperatures, the requirements of precision and accuracy of the measurement, and the characteristics of the combustion furnace that normally must keep the material in motion. This research proposes an intelligent sensor that allows its remote use and guarantees the constant and safe monitoring of the variable, as well as its conditioning and communication. The sensor is composed of a digital camera aligned with the flame capable of capturing video frames continuously and safely. These digital images are processed by a categorization module previously trained with a convolutional neural network, and the result is transmitted to the control unit. In tests on a real furnace, high performance and reliable operation sufficient for industrial implementation were proved.

1. Introduction

The most widely used purifying agent by humans is activated carbon. This is due to its high capacity of absorption of toxic substances, fats, detergents, and vegetables, among others (mainly organic), which it achieves thanks to its porosity and crystalline structure [1]. This porosity is very high, with microcores of less than 2 nanometers in radius, which allows high performance in purification processes [2]. Activated carbon is produced from organic material either by physical activation or chemical activation, industrially the physical process is preferred at very high temperatures, which changes its internal structure (reducing the pore size) [3]. To produce carbon activation requires a thermal (or chemical, but the efficiency of the process and its cost is lower thermally) decomposition process of organic material, which in many cases is made up of plant waste in agricultural production plants such as sugar cane fields, under careful air control [4]. The control of the process variables is very important for the quality of the product. In the material to be processed, the oxygen, hydrogen, and nitrogen content must be eliminated (controlled to low values) to proportionally increase the carbon content of the material. In addition, production is carried out in large furnaces in which the amount of oxygen as a combustion comburent must be controlled at all times, as well as the heating rate and the time spent in the furnace [5]. It has been demonstrated that the continuous and precise control of these variables is a highly determinant factor in the final quality of the activated carbon [6]. However, it must be considered that the working temperature is very high (generally higher
than 300 degrees Celsius), which makes the direct detection of the process variables difficult, particularly of oxygen if the transducers traditionally used to build sensors are considered. Traditionally, in production plants, the temperature of the organic material in the process is measured inside the furnace using thermocouples, often intermittently by an operator through access points in the furnace, or even at a single point. More automated processes include continuous measurement at different points utilizing sensors installed in the furnace that transmit the information to the control center, where it is filtered and averaged for process adjustment [7, 8]. This type of measurement, where direct contact is maintained with the process material, is known as contact measurement. It is a fairly simple measurement scheme, and easy to implement, but it can be very dangerous for the operator since the process itself involves working with high temperatures, and with a furnace that needs to be in a continuous movement of the processed material. Many of these strategies provide only localized information of the temperature in the material, which constitutes partial feedback of the real state of the product. In cases that implement multiple measurement points, this information is supplemented by the development of behavioral thermal models that can extend the partial feedback to full state feedback. These models, however, must be adjusted and tuned for each case [9, 10].

Non-contact measurement schemes are also used industrially. In this type of system, greater operator safety can be guaranteed, and in general, the measurement schemes support continuous measurement, and the sensors have a much longer service life [11, 12]. Among the industrially used sensors of this type are infrared thermometers, colorimetric thermometers, and thermal imagers, whose principle of operation can be extended to other variables. The most common system is the infrared thermometer, which operates by detecting the infrared radiation of the element whose temperature is to be estimated. The sensor’s processor converts the detected radiation level to an electrical signal (usually a proportional voltage), which is coded to temperature. The colorimetric thermometer also makes use of the infrared signal emitted by the element, but in this case, it uses two adjacent infrared bands, and the detected ratio between them is scaled to a temperature value. These two sensors calculate the temperature at a point on the element using average settings, a measurement that can be affected by the conditions of the measurement environment. The third scheme has a different approach, these thermal cameras can produce an image of the infrared radiation produced by the entire element of interest (not just a single point), so they are less affected by the environment, and by processing this image can determine the temperature in all elements of the image [13, 14].

This research focuses on the problem of oxygen sensing. This variable is traditionally measured with direct contact schemes, using specialized point measurement equipment capable of indicating specific values inside the furnace chamber. They typically use a probe that is introduced into the hot environment to sample the air inside. This point measurement scheme does not provide global information on the behavior of the oxygen inside the furnaces, nor how it is distributed, or if the value taken is characteristic of the gas behavior, so the control in the carbonization process can lead to production failures. Another problem detected in the cases analyzed is that the furnace has a dynamic necessary to keep the material inside it in motion, in the target production plant it is a continuously rotating cylindrical furnace (with control of the rotation speed), which makes the punctual reading with this type of instruments complex and dangerous for the operators. Again, these point sensing schemes require the development and adjustment of behavioral models, specific to each case [15, 8]. As with temperature, the guarantee of oxygen behavior inside the furnace can only be achieved by a sensor capable of taking a global reading of the environment inside the furnace, ideally also by remote sensing, and with the ability to process on-site and transmit to the control unit the information in real-time and continuously [16]. We propose an intelligent sensor capable of identifying the behavior of the oxygen inside the furnace using a digital camera installed at a distance from the process, but focusing on the burner flame, capable of identifying in real-time the oxygen content from an image classification model formed by a convolutional neural network (CNN), estimate the necessary control values, and wirelessly transmit the information to the control unit [17]. It is an embedded system that digitally processes the image before its propagation through the deep learning model, and the output information of the model determines the behavior of the oxygen [18]. This intelligent sensor has enormous advantages over the schemes
currently used by the plant, including lower system costs (including development, maintenance, and operation) compared to the current probe solution, continuous and global measurement of the variable, and a safe working environment for the operators.

2. Problem statement
The production of activated carbon requires that the organic material is reduced in hydrogen, oxygen, and nitrogen content through a thermal decomposition process. This process increases the proportions of carbon and allows the formation of micropores on the surface. In the production plant under study, the process is carried out inside a rotating cylindrical furnace with continuous control of the fuel in the burner (natural gas), furnace rotation speed, residence time, and oxygen input to the combustion. The oxygen level control is traditionally carried out manually by operators who regulate the access to the burner using a valve, visually verifying the flame behavior (size and color). This regulation is based on the principle that oxygen is directly involved in combustion, and therefore determines the characteristics of the flame. Under this hypothesis, the plant has operated and produced material in the previous history. Therefore, as a way to improve product quality, reduce accidents and costs, an intelligent sensing system that takes advantage of the same principle is proposed. Such a system will replace the visual examination of the operator with a digital camera linked to an embedded processing system, which will be able, at least in this first stage, to identify four reference categories concerning the percentage of oxygen in the thermal process.
The four reference categories identified as sensor outputs correspond to four specific flame states calibrated in the plant with the probe measurement instruments and supported by the expertise of production plant operators and engineers. These were categorized as follows:

- Category 0: Flame with 0% air.
- Category 1: Flame with 40% air.
- Category 2: Flame with 80% air.
- Category 3: Flame with 100% air.

The intelligent part of the intelligent sensor is in charge of categorizing the camera images in real-time. To conform this model, we proposed a convolutional architecture type NASNet (Neural Architecture Search Network), which, although it was developed to obtain high performance with CIFAR-10, in our tests it demonstrated superior performance compared to other architectures such as DenseNet or ResNet, and with a small number of parameters, which facilitated its implementation on an embedded device. We used NASNet Mobile, but without any set of pre-trained parameters (own training).

For training purposes, a dataset of 500 images in each of the four categories is available. These images correspond to real operation cases captured by the camera during the operation of the furnace, and with the support of instruments and qualified personnel from the production plant. Since the images correspond to actual plant operation, they include material and dust variations inside the furnace that ultimately help to increase the categorization capability of the model.

3. Methods
The dataset was constructed from images taken by the sensor camera itself during normal operation, and under the supervision of expert personnel (figure 1). A total of 500 images were stored in each of the categories, i.e., 2000 images in total, of which 70% were used for training and 30% for validation. The images were randomly shuffled before starting the training and were also randomly separated into two groups. To train the neural model (and later to propagate the network during sensor operation) the images were scaled to a size of 256x256 pixels, which was shown to considerably reduce the computational cost without reducing the classification performance of the model.
Figure 1. Training and validation dataset of the categorization model. (a) Category 0: Flame with 0% air, (b) Category 1: Flame with 40% air, (c) Category 2: Flame with 80% air, and (d) Category 3: Flame with 100% air.

The model was built in Keras and Python, and the stochastic gradient descent was used as the optimization function for the compilation. To evaluate the error, the categorical cross-entropy function was used as a loss function. During training, different metrics were calculated, both with the training data and with the validation data. The fitted model was also validated with specific performance metrics. Video capture and image preprocessing were also performed in Python with the help of OpenCV. The sensor was implemented on a DragonBoard 410c platform from Arrow, which has a Qualcomm Snapdragon 410 ARM Cortex A53 quad-core processor with a clock speed of up to 1.2 GHz per core, Qualcomm Adreno 306 GPU, integrated digital camera support, and Linux Debian was configured as the operating system. A router was also used to facilitate WiFi communication.

4. Results

The code for the embedded system was developed entirely in Python (3.7.3). Keras (2.2.4) was used to propagate the convolutional model, and all image processing was done with OpenCV (4.1.0.25). Specific libraries such as Scikit Learn (0.20.3), NumPy (1.16.4), Scipy (1.3.0), and Pandas (0.24.2) were also used. The convolutional model had a total of 4,273,944 parameters, of which 4,237,206 were adjusted during training and fine-tuning of the model. The final version of our model was trained and evaluated over 9 epochs, during which its performance was evaluated with known images (training data) and unknown images (validation data). The evaluation during this final training was performed by
calculating the Accuracy and loss in each case. Figure 2 shows the results, here we can appreciate the high Accuracy value of the model for both training and validation data (green and red curves respectively), and how similarly the losses with the two datasets remain low (blue and orange curves). The model does not reflect overfitting or underfitting and demonstrates a high degree of tunability.

![Training Loss and Accuracy (NASNet)](image)

**Figure 2.** Performance of the model during final training.

The categorization capacity of the model was evaluated using the confusion matrix (figure 3), and the Receiver Operating Characteristics (ROC) curve (figure 4). The precision, recall, and F1-score metrics were also determined (figure 5). In all cases, the high performance of the model in correctly identifying the propagated images was observed. The average value of the three metrics (precision, recall, and F1-score) was 99%, and the individual values per category were never below 97% for any of them. This behavior can be visually verified in both the Confusion Matrix and the ROC curve.

5. Conclusions

This paper presents the development of an intelligent sensor for oxygen estimation for use in an activated carbon production plant. The core of the sensor is based on a neural model that categorizes images from a digital camera using a NASNet (Neural Architecture Search Network) architecture. The system is trained with images of the carbonization process in the industrial plant and achieves an accuracy of 99%. The sensor is implemented on an embedded system running Linux Debian on an ARM Cortex A53 quad-core processor. A communication system over WiFi is also implemented. The performance tests on the prototype demonstrate its high performance, and as future work, the need for evaluation in real conditions for industrial use is raised.
Figure 3. Confusion Matrix.

Figure 4. ROC Curve. (a) Receiver Operating Characteristics. (b) AUC (Area Under the Curve).

Figure 5. Metrics precision, recall, and F1-score.
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