Research Article

A Novel Segmentation Method for Furnace Flame Using Adaptive Color Model and Hybrid-Coded HLO

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1. Introduction

Nowadays, combustion furnaces have been widely applied in different fields of industry [1], such as coal-fired power plants [2], steelmaking [3], waste incineration [4], and cement production [5]. Since the combustion flame is one of the most direct characteristics that reflect the combustion status inside the industrial furnace, the accurate detection of combustion states can effectively help operators adjust combustion strategies to improve combustion utilization and ensure safe operation. Therefore, various approaches were developed and applied to measure the combustion flame inside the industrial furnace [6–8], such as spectral analysis technology [6], optical fiber sensor technology [7], and temperature sensor technology [8].

With the development of machine vision, image processing technology has been gradually applied to detect and segment the combustion flame [9] because it has a high detection accuracy for flame segmentation. Wang et al. [10] present a new flame segmentation color model based on HSI and backpropagation, which transforms the RGB color image captured by the CCD into the HSI color image, and then the BP neural network is adopted to effectively segment the characteristics of combustion flame. Celik et al. [11] propose a generic flame segmentation color model that combines foreground object information with color pixel statistics of combustion flame, in which the foreground information is extracted by using adaptive background subtraction algorithm and then verified by the statistical flame color model to determine whether the segmented foreground object is a flame candidate information or not. Zhang et al. [12] use the nonlinear partial least-squares colorimetry and Monte Carlo with iterative optimization to research the actual combustion status for obtaining a flame distribution. Chen et al. [13] present a new color space model based on scale invariant feature transform (SIFT), in which the SIFT algorithm is introduced to extract the feature descriptors of combustion flame for achieving better
adaptability and robustness model. Wang et al. [14] develop a convolutional neural network approach based on adaptive pooling, which effectively avoids the blindness in the traditional feature extraction process and the learning of invalid features in the convolutional neural network, and the experiment results show that the developed approach has a higher segmentation rate. Qiu et al. [15] propose an unsupervised classification measurement approach based on the convolutional autoencoder, in which the principal component analysis (PCA) and the hidden Markov model (HMM) are adopted to monitor the combustion condition with the uniformly spaced flame image. Zhang et al. [16] propose a new adaptive color model with a double threshold to improve the segmentation efficiency and detection accuracy of the combustion flame. Hashemzadeh and Zadeh [17] develop a robust color model by using K-medoids to reliably detect all candidate flame regions in a scene, which provides high detection accuracy and low false detection rate for flame recognition. Ye et al. [18] propose a new flame segmentation approach with wavelet analysis to detect smoke and flame simultaneously for color dynamic scene, which provides high detection accuracy and low false detection rate for flame recognition. Ye et al. [18] propose a new flame segmentation approach with wavelet analysis to detect smoke and flame simultaneously for color dynamic scene, which provides high detection accuracy and low false detection rate for flame recognition.

As image segmentation contains multiple factors, it is difficult to obtain the best segmentation parameters by trial and error. Therefore, a variety of metaheuristic algorithms, such as particle swarm optimization [21], differential evolution [22], memetic algorithm [23], and genetic algorithm [24], have been adopted to search the optimal parameters for obtaining the best segmentation effect. However, the combustion states inside the industrial furnace, as well as the RGB components of combustion flame, change according to the production needs [25], which further challenges the optimal set of model parameters but is not considered in the previous works. To tackle this problem, the weight coefficients of RGB components and segmentation threshold are both considered as the variables to design the adaptive color model in this work. The segmentation threshold is the discrete number, which can be found out more efficiently by the binary-coding algorithm [16, 26]; the weight coefficients are continuous variables between 0 and 1, which are introduced to enhance the robustness of the model for combustion states. Thus, the objective function of the proposed adaptive color model is a hybrid-coding problem. The hybrid-coded human learning optimization (HcHLO) [27] is a novel and powerful framework for solving hybrid-coded problems, which achieved the so-far best-known results on a set of hybrid-coded benchmark problems. Therefore, this paper proposes a novel segmentation method for furnace flame using adaptive color model and hybrid-coded HLO, in which a new adaptive color model with mixed variables (NACMM) is presented to effectively segment the flame pixels of different combustion states, and an adaptive hybrid-coded human learning optimization (AHcHLO) is developed to find the best optimized parameters of NACMM for guaranteeing the best performance. Regarding this proposed NACMM, two objective functions are adopted as the evaluation index to evaluate the segmentation accuracy and reduce the structural risk.

The rest of the paper is organized as follows. Section 2 presents the proposed AHcHLO in detail. Section 3 describes the furnace flame segmentation based on the NACMM with AHcHLO. Section 4 gives the performance comparison of the proposed AHcHLO with other recent algorithms and the comparison results of the segmentation simulation of furnace flame. Finally, conclusions are drawn in Section 5.

2. Adaptive Hybrid-Coded Human Learning Optimization

The HLO [28] algorithm adopts the three learning operators, i.e., the random learning operator (RLO), the individual learning operator (ILO), and the social learning operator (SLO), to search for the optimal solution. Nowadays, HLO has been successfully used to solve the various types of optimization problems, such as furnace flame recognition [16], image segmentation [26], knapsack problems [29], engineering design problems [27, 30], optimal power flow calculation [31], extractive text summarization [32], financial markets forecasting [33], scheduling problems [34], and intelligent control [35]. To solve the mixed variables of NACMM more effectively, an adaptive strategy is developed to further enhance the search ability of AHcHLO.

2.1. Initialization. Like the standard HcHLO [27], the proposed AHcHLO adopts the binary-real mixed coding framework to represent the individual’s knowledge, in which continuous parameters are directly represented as real-coded variables, which are randomly initialized between the lower bound and upper bound, while the Boolean or discrete parameters are coded as a binary string, which is stochastically initialized with “0” or “1.” Thus, an individual of AHcHLO is represented as

\[
x_i = \left[ \begin{array}{c} R_1 \ R_2 \ \ldots \ R_{iM_r} \ B_1 \ B_{i2} \ \ldots \ B_{iM_b} \\ \text{Array(R)} \ \text{Array(B)} \end{array} \right], \]

where \( x_i \) denotes the \( i \)-th individual; Array(R) and Array(B) store the real-coded variables and the binary/discrete variables of solutions, respectively. \( N \) is the size of population, and \( M_r \) and \( M_b \) denote the lengths of the real-coded variables and binary strings, respectively. The whole dimension of solutions is \( M = M_r + M_b \). Initially, the elements of each individual in Array(R) and Array(B) are randomly initialized. After generating \( N \) individuals, an initial population is obtained as
2.2. Learning Operators

2.2.1. Random Learning Operator. Random learning [36] usually exists in human learning as there is no prior knowledge of problems at the beginning. With the progress of learning, the random learning strategy remains to keep the peculiar creativity of human beings. Inspired by the random learning strategy, the random learning operator (RLO) is used in AHcHLO, in which real-coding variables $R_{ij}$ are operated by (3) while the bits of binary strings are operated by (3) while the bits of binary strings are generated by (4).

\[ R_{ij} = x_{\min,j} + r_1 \times (x_{\max,j} - x_{\min,j}), \quad (3) \]

\[ B_{ij} = \text{Rand} (0, 1) = \begin{cases} 0, & 0 \leq r_2 \leq 0.5, \\ 1, & \text{else} \end{cases}, \quad (4) \]

where $x_{\min,j}$ and $x_{\max,j}$ are the lower bound and upper bound of real-coded variable $j$; $r_1$ and $r_2$ are two independent random numbers between 0 and 1.

2.2.2. Individual Learning Operator. Individual learning [37] is an efficient learning strategy by adopting the obtained personal experience to avoid the same mistakes. To imitate the individual learning strategy, the personal best solutions are saved in the individual knowledge database (IKD) of AHcHLO, which is represented as

\[ IKD = \begin{bmatrix} i_{kd_1} \\ i_{kd_2} \\ \vdots \\ i_{kd_i} \\ \vdots \\ i_{kd_N} \end{bmatrix}, \quad 1 \leq i \leq N, \quad (5) \]

\[ ikd_i = \begin{bmatrix} i_{kd_{11}} \\ i_{kd_{12}} \\ \vdots \\ i_{kd_{ip}} \\ \vdots \\ i_{kd_{iT}} \end{bmatrix} = \begin{bmatrix} i_{k_{a1}} & i_{k_{B_{12}}} & \ldots & i_{k_{B_{1j}}} & \ldots & i_{k_{B_{1M_i}}} \\ i_{k_{a2}} & i_{k_{B_{22}}} & \ldots & i_{k_{B_{2j}}} & \ldots & i_{k_{B_{2M_i}}} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ i_{k_{ap}} & i_{k_{B_{p2}}} & \ldots & i_{k_{B_{pj}}} & \ldots & i_{k_{B_{pM_i}}} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ i_{k_{aq}} & i_{k_{B_{q2}}} & \ldots & i_{k_{B_{qj}}} & \ldots & i_{k_{B_{qM_i}}} \end{bmatrix} \]

\[ Array(ik_{up}) \]

\[ Array(ik_{it}) \]

\[ R_{ij} = i_{k_{B_{pq}}} + I_{L} \times r_3 \times (sk_{q_{R_{ij}}} - i_{k_{B_{pq}}}), \quad (7) \]

\[ B_{ij} = i_{k_{B_{pq}}}, \quad (8) \]

where $I_{L}$ is the linear individual learning factor and $r_3$ is a stochastic number between $-1$ and $1$. 

\[ \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_i \\ \vdots \\ x_N \end{bmatrix} = \begin{bmatrix} r_{11} & R_{12} & \ldots & R_{1j} & \ldots & R_{1M_i} \\ r_{21} & R_{22} & \ldots & R_{2j} & \ldots & R_{2M_i} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ r_{ni} & R_{i2} & \ldots & R_{ij} & \ldots & R_{iM_i} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ r_{N1} & R_{N2} & \ldots & R_{Nj} & \ldots & R_{NM_i} \end{bmatrix} \]

\[ Array(R) \]

\[ Array(ik_{it}) \]
2.2.3. Social Learning Operator. Social learning [38] plays an important role in an integrated social environment because it allows humans to copy the best information in the population, and therefore it can greatly improve learning efficiency and effectiveness. To imitate the social learning strategy, the best knowledge of population is stored in the social knowledge data (SKD) as

\[
SK\ D = \begin{bmatrix}
    sk_{d1} \\
    sk_{d2} \\
    \vdots \\
    sk_{dH}
\end{bmatrix} = \begin{bmatrix}
    sk_{1B_1} & sk_{1B_2} & \cdots & sk_{1B_r} & \cdots & sk_{1R_1} & \cdots & sk_{1R_M} \\
    sk_{2B_1} & sk_{2B_2} & \cdots & sk_{2B_r} & \cdots & sk_{2R_1} & \cdots & sk_{2R_M} \\
    \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \ddots & \vdots \\
    sk_{R_1B_1} & sk_{R_1B_2} & \cdots & sk_{R_1B_r} & \cdots & sk_{R_1R_1} & \cdots & sk_{R_1R_M} \\
    \end{bmatrix},
\]

where \( sk_{qB_i} \), \( sk_{qR_i} \) denote the \( j \)-th real-coded/binary knowledge of \( q \)-th best solution in the SKD, and \( H \) is the size of SKD.

When AHcHLO performs the social learning operator (SLO) to generate new candidate solutions, the linear social learning operator (ISLO) is used to operate the continuous variables in Array\((sk_R)\) as (10), and the standard social learning operator in HLO is adopted to deal with the bits in Array\((sk_R)\) as (11).

\[
R_{ij} = sk_{qR_i} + S_L \times r_4 \times (sk_{qR_i} - i k_{R_j}),
\]

(10)

\[
B_{ij} = sk_{qB_j},
\]

(11)

where \( S_L \) stands for the linear social learning factor and \( r_4 \) is a random number between 0 and 1.

2.3. Adaptive Strategy. Obviously, the linear individual learning factor \( I_L \) and the linear social learning factor \( S_L \) are extremely important because they directly determine the learning abilities of IILO and ISLO, respectively. In the standard HcHLO, these two parameters, i.e., \( I_L \) and \( S_L \), are both set as constants, and the recommended values are 1 and 2; that is, the individual always learns and solves problems with the same capability or level of proficiency, which is not true for real human learning. Qamar et al. [39] points out that the learning strategies of humans change as the quality of the sensory evidence varies, and Zimmermann and Martinez-Pons [40] indicate that both convergent and discriminative validity exist in the construct of human learning. Humans usually search for the best possible knowledge in a wide range as they lack prior knowledge of problems at the beginning [41], and they adjust and reduce their learning strategies to approach optimal knowledge based on the last learning result with the progress of learning [40]. As Scarbrough et al. [42] state, the adaptive learning strategy can effectively exploit the accumulated knowledge of human beings in situations that are uncertain and complicated. Inspired by these discoveries, the adaptive strategies for \( I_L \) and \( S_L \) are developed in AHcHLO to improve the search efficiency and solution quality of the algorithm, which is presented as

\[
I_L = I_{L,\text{max}} - \frac{I_{L,\text{max}} - I_{L,\text{min}}}{I_{\text{te,max}}} \times I_{\text{te}},
\]

(12)

\[
S_L = S_{L,\text{max}} - \frac{S_{L,\text{max}} - S_{L,\text{min}}}{I_{\text{te,max}}} \times I_{\text{te}},
\]

(13)

where \( I_{L,\text{min}} / S_{L,\text{min}} \) and \( I_{L,\text{max}} / S_{L,\text{max}} \) are the minimum and maximum values of \( I_L / S_L \), respectively; \( I_{\text{te}} \) and \( I_{\text{te,max}} \) are the current iteration number and maximum iteration number of searches, respectively.

With the introduction of the adaptive \( I_L \) and \( S_L \) strategy, the proposed AHcHLO can efficiently explore the interesting solution areas more widely at the beginning of iterations, search for the optimal candidate solution in a more suitable range at the middle of the search process, and perform the accurate local search to find the optima at the end of generations. Therefore, the proposed AHcHLO can achieve a practically ideal trade-off between exploration and exploitation, and the optimization search ability of AHcHLO is significantly enhanced.

2.4. Updating of the IKD and the SKD. Since AHcHLO is designed for solving single-objective problems, the sizes of IKDs and SKD are both set to 1 as recommended in [43]. After a new population is generated, the fitness values of all individuals are calculated according to the predefined fitness function to update the IKDs. The new candidate replaces the original solution in the IKDs only if its fitness value is superior. Otherwise, the original solution in the current IKDs will remain. Similarly, the new candidate is saved to replace the current one in the SKD only if it has a better fitness value. Besides, the IKD is reinitialized to further enhance the diversity if it is not updated in 100 generations as [27].

2.5. Implementation of AHcHLO. In summary, AHcHLO uses three learning operators, i.e., the random learning
where $g(x, y)$ represents the gray value of grayed image in the pixel position $(x, y)$; $f_R(x, y)$, $f_G(x, y)$, and $f_B(x, y)$ are the RGB gray values of the original image in the pixel position $(x, y)$, respectively; and $k_r$, $k_g$, and $k_b$ are the weight coefficients of RGB components, and $k_r = k_g = k_b = (1/3)$.

The relationship between combustion states and RGB gray values is not considered in the previous works, which influences the segmentation accuracy of combustion flame. To better achieve the separation of flame pixels, the adaptive weight coefficients are considered in this work. Moreover, five image graying methods, i.e., average method ($k_r = k_g = k_b = (1/3)$), maximum method (selecting the maximum gray values of RGB components), weighted average method 1 ($k_r = 0.7, k_g = 0.15, k_b = 0.15$), weighted average method 2 ($k_r = 0.15, k_g = 0.7, k_b = 0.15$), and weighted average method 3 ($k_r = 0.15, k_g = 0.15, k_b = 0.15$), are used to gray flame images I-IV for intuitively understanding these characteristics, which are shown in Figures 2–5. By comparing the characteristics of flame images I-IV under different image graying methods, the following conclusions can be made:

1. Figure 2 clearly confirms that the maximum method obtains an ideal grayscale image because the $f_R(x, y)$ gray values are the largest, the $f_G(x, y)$ gray values are the second, and the $f_B(x, y)$ gray values are the least. The maximum method is also the special case of the weighted average method; i.e., $k_r = 1, k_g = 0, k_b = 0$.

2. Figure 3 demonstrates that weighted average method 2 achieves the best grayscale image because the color of combustion flame becomes brighter. Meanwhile, compared with weighted average method 1, weighted average method 2 reduces the interference of external light.

3. Figure 4 explicitly proves that weighted average method 3 obtains the best grayscale image, which effectively reduces the interference of R gray values around the combustion flame. In particular, for the maximum method, Figure 4(b) does not benefit from the separation of flame pixels.

4. Figure 5 effectively confirms that the effects of grayscale image under the five methods are almost the same because the color of combustion flame is white; that is, the RGB gray values are all close to the maximum, and there is no color interference of external light.

3.2. New Adaptive Color Model with Mixed Variables. The above comparison results clearly show that the flame images of different combustion states prefer different image graying methods to obtain the best effect of grayscale images because of the change of RGB gray values of combustion flame. Specifically, the R gray values are very significant for discriminating between “flame” and “nonflame” regions when the temperature is relatively low, and the G and B gray values are more conducive to segmenting the flame pixels with the increase of the temperature. Therefore, a new adaptive color

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Complexity
(1) Initialize population $X$
(2) Calculate Fitness Function
(3) Initialize the $IKD$s and $SKD$
(4) while the stop criterion is not satisfied do
(5) for $i = 1$ to $N$ do
(6) for $j = 1$ to $M$ do
(7) if $(r \geq 0$ and $r < pr)$ then
(8) Generate $R_{ij}$ as equation (3) and $B_{ij}$ as equation (4)
(9) else if $(r \geq pr$ and $r < pi)$ then
(10) Generate $R_{ij}$ as equation (7) and $B_{ij}$ as equation (8)
(11) else if $(r \geq pi$ and $r < 1)$ then
(12) Generate $R_{ij}$ as equation (10) and $B_{ij}$ as equation (11)
(13) end if
(14) end for
(15) end for
(16) Calculate Fitness Function
(17) Update the $IKD$s and $SKD$
(18) Calculate $I_L$ and $S_L$ according to equations (12) and (13)
(19) end while

Algorithm 1: Pseudocode for AHcHLO.

Figure 1: The four flame images of different combustion states: (a) I; (b) II; (c) III; (d) IV.

Figure 2: The comparison results of flame image I under different methods: (a) average method; (b) maximum method; (c) weighted average method 1; (d) weighted average method 2; (e) weighted average method 3.

Figure 3: The comparison results of flame image II under different methods: (a) average method; (b) maximum method; (c) weighted average method 1; (d) weighted average method 2; (e) weighted average method 3.
model with mixed variables (NACMM) is proposed for adapting to the different combustion states, in which the weight coefficients of RGB components, i.e., $k_R$, $k_G$, and $k_B$, and segmentation threshold $t_1$ are simultaneously adjusted. For a given flame image in NACMM, the corresponding grayed image $g_1$ is obtained by the adaptive weighted average method as (16), in which the median filtering method, i.e., (17), is adopted to effectively smooth the interference points and maintain the edge information of combustion flame because of the noise interference factors in the original image.

$$g_1(x, y) = k_R \times f_{2R}(x, y) + k_G \times f_{2G}(x, y) + k_B \times f_{2B}(x, y), \quad (16)$$

where $k_R$, $k_G$, and $k_B$ are the weight coefficients of RGB components, and $k_R + k_G + k_B = 1$; $f_{2R}(x, y)$, $f_{2G}(x, y)$, and $f_{2B}(x, y)$ are the RGB gray values of the filtered flame image in the pixel position $(x, y)$, respectively; and $n_1$ is the size of filter window and is set to 5 in this work.

Then, the preset threshold variable $t_1$ is used to effectively segment the grayed image $g_1$, and the flame/nonflame pixels are marked as white/black pixels, respectively, which is presented as

$$g_2(x, y) = \begin{cases} 
1, & \text{if } g_1(x, y) > t_1, \\
0, & \text{else}, 
\end{cases} \quad (18)$$

where $g_2$ represents the processing result of the segmented flame image.

In NACMM, the preset weight coefficients $k_R$, $k_G$, and $k_B$ are continuous distribution optimization problems between 0 and 1, and the preset threshold variable $t_1$ is a discrete variable optimization problem between 0 and 255. The previous works [16, 26] prove that the binary-coding algorithm can calculate the segmentation threshold $t_1$ more efficiently; that is, the objective function of NACMM is a hybrid-coding problem.

### 3.3. The NACMM with AHcHLO

Then, the proposed AHcHLO is performed to search for the best values of the parameters $t_1$, $k_R$, $k_G$, and $k_B$. The objective function $Obj_1$ is calculated by the sample pixels to evaluate the quality of NACMM. Note that the NACMM optimized only by using $Obj_1$ still has a structural risk because of the limitation of the number of sample pixels. Specifically, the preset threshold $t_1$ within a certain range $[T_1, T_2]$ can achieve the separation of sample pixels, but the limit thresholds $T_1$ and $T_2$ cannot effectively separate the pixels on the edge of combustion flame. To effectively reduce this structural risk, the objective function $Obj_2$ is adopted to further optimize the preset threshold $t_1$ for obtaining better NACMM when the values of objective function $Obj_1$ are equal. Therefore, the best NACMM with optimal parameters $t_1$, $k_R$, $k_G$, and $k_B$ is obtained through the evaluation of objective functions $Obj_1$ and $Obj_2$.
3.3.1. Construction of Objective Function \(Obj_1\). The objective function \(Obj_1\) is the proportion of the number of correctly classified sample pixels (flame and nonflame) to the total number of sample pixels, and the higher value of \(Obj_1\) indicates better NACMM, which is given by

\[
Obj_1(t_1, k_g, k_G, k_B) = \frac{N_1 + N_2}{M_1 + M_2} \times 100\%,
\]

where \(N_1\) and \(N_2\) are the number of correctly classified flame and nonflame sample pixels, respectively; \(M_1\) and \(M_2\) represent the total number of flame and nonflame sample pixels, respectively. The flame/nonflame pixels from the filtered flame image are extracted to construct the flame/nonflame sample pixels, respectively. As the sample pixels have a greater impact on the quality of NACMM, they are manually selected from different parts of the flame/nonflame regions. The examples of selected flame/nonflame sample pixels for flame image I are given in Figures 6(b) and 6(c), in which the size of each selected sample image is \(n_2 \times n_2\), the flame/nonflame sample images are selected 20 times, respectively, and therefore \(M_1 = M_2 = 20 \times n_2 \times n_2\).

3.3.2. Construction of Objective Function \(Obj_2\). For the grayed image \(g_1\), the total intensity levels can be expressed as \(L\) lying in the range \([t_0, t_2]\) where \(t_0\) and \(t_2\) are the minimum and maximum gray intensity levels, respectively. Further, let the pixel number of \(L\) intensity level and all intensity levels be denoted as \(E_L\) and \(E\), respectively. Because there are only two classes of pixels for the flame image, i.e., the nonflame pixels and the flame pixels, the flame pixels in \(g_1\) can be efficiently segmented and extracted based on their gray intensity levels and the preset threshold variable \(t_1\); that is, the nonflame pixels are from \(t_0\) to \(t_1\), and the flame pixels are from \(t_1\) to \(t_2\). Therefore, the objective function \(Obj\) is calculated by the Otsu method as (20)–(23), and the higher value of \(Obj_2\) indicates better NACMM.

\[
Obj_2(t_1) = \sum_{c=1}^{2} p_c(t_1) \times [u_c(t_1) - u_c]^2,
\]

\[
u_c(t_1) = \frac{\sum_{L=t_{c-1}}^{t_c} L \times (E_L/E)}{p_c(t_1)},
\]

\[
p_c(t_1) = \frac{\sum_{L=t_{c-1}}^{t_c} E_L}{E},
\]

\[
u_c = \frac{\sum_{L=t_0}^{t_2} L \times E_L}{E},
\]

where \(c\) denotes the class of pixels, \(c \in \{1, 2\}\); that is, \(c = 1\) and \(c = 2\) are the classes of nonflame pixels and flame pixels, respectively; \(u_c(t_1)\) and \(p_c(t_1)\) represent the probability of mean and occurrence of class \(c\), respectively; and \(u_c\) is the total mean of all classes.

In summary, the NACMM with AHC-HLO is optimized by two objective functions for improving the segmentation accuracy and reducing the structural risk. Firstly, the flame/nonflame sample pixels are constructed from the flame image, and the segmentation threshold \(t_1\) and the weight coefficients, i.e., \(k_g, k_G, k_B\), are initialized as binary strings and real-coded variables, respectively. On this basis, the filtered flame image is segmented based on the initialized parameters, and the corresponding objective function values \(Obj_1/Obj_2\) are calculated. Then, the AHC-HLO is used to generate new parameters, and the corresponding candidate objective function value \(Obj_1'\) is calculated to evaluate the quality of NACMM. The new candidate is saved to replace the current one in the IKDs and SKD only if it has a better value of the objective function. Note that the corresponding objective function \(Obj_2'\) needs to be calculated and compared with \(Obj_2\); if the value of objective function \(Obj_2'\) is equal to that of \(Obj_2\), which can further obtain better threshold \(t_1\) for reducing the structural risk of NACMM. When the termination conditions are met, the optimal parameters \(t_1, k_g, k_G, k_B\) are output to obtain the best NACMM. Finally, the best NACMM is adopted to segment the flame image, and the flame/nonflame pixels are marked as white/black pixels, respectively. The furnace flame segmentation based on the NACMM with AHC-HLO is summarized in Figure 7.

4. Experimental Results and Discussion

In this section, the proposed AHC-HLO was firstly used to solve the benchmark functions for evaluating its optimization ability. Then, the segmentation simulation for furnace flame based on the NACMM with AHC-HLO was performed to verify its effectiveness and feasibility.

4.1. The Benchmark Functions. A total of 14 optimization problems with mixed variables [27] were adopted as the benchmark functions to evaluate the performance of the proposed AHC-HLO, and the numerical results of AHC-HLO were compared with the five recent optimization algorithms, i.e., hybrid-coded human learning optimization algorithm (HcHLO) [27], adaptive simplified human learning optimization algorithm (ASHLO) [43], improved adaptive human learning optimization algorithm (IAHLO) [30], scale-free particle swarm optimization (SFPSO) [46], and hybrid particle swarm optimization with adaptive learning (ALPSO) [47]. A set of fair parameters obtained by a simple trial-and-error procedure was adopted for AHC-HLO, that is, \(pr = 0.1\), \(pi = 0.85\), \(I_{\text{max}} = 2.0\), \(I_{\text{min}} = 0.2\), \(S_{\text{max}} = 3.0\), and \(S_{\text{min}} = 1.0\). The population size and the maximal iteration number of AHC-HLO were set as those recommended in [27]. For a fair comparison, HcHLO, ASHLO, IAHLO, SFPSO, and ALPSO used the recommended parameter values, and the maximal number of function calculations was the same as that of AHC-HLO. Besides, if the gap between the found one and the theoretical optima is less than \(10^{-6}\), the search will be terminated as suggested in [48]. All the cases ran 100 times independently.
Load the flame image

Begin

Set the control parameters and initialize the population of optimized parameters $t_1, k_R, k_G, k_B$ randomly

Separate flame pixels and calculate objective function $Obj_1$ and objective function $Obj_2$

Perform AHcHLO algorithm to generate new candidate optimized parameters $t_1, k_R, k_G, k_B$

Calculate the objective function $Obj'_1$ of corresponding candidate optimized parameters

Yes

$Obj_1 = Obj'_1$?

No

Calculate $Obj'_2$ and compare it with $Obj_2$

Return better parameters $t_1, k_R, k_G, k_B$

Terminate the iteration?

Yes

Return best optimized parameters $t_1, k_R, k_G, k_B$

The best NACMM is used to segment the flame image

Output the segmented flame image

End

Figure 6: Extracting sample pixels from flame image I: (a) original flame image; (b) flame sample pixels; (c) non-flame sample pixels.

Figure 7: Flowchart of proposed furnace flame segmentation method.
| Fun     | Metric | AHcHLO | HcHLO | ASHLO | IAHLO | SFPSO | ALPSO |
|---------|--------|--------|-------|-------|-------|-------|-------|
| Best    | 87.500000 | 87.500000 | 87.500000 | 87.500000 | 87.500000 | 87.500000 |
| Mean    | 87.500000 | 87.500000 | 87.500000 | 87.500000 | 87.500000 | 87.500000 |
| **F1**  | Std 0.00E + 00 | 3.02E - 08 | 0.00E + 00 | 3.02E - 08 | 0.00E + 00 | 3.02E - 08 |
|         | t-test     |        |       |       |       |       |       |
|         | W-test     |        |       |       |       |       |       |
| Best    | 7.667180  | 7.667180 | 7.667180 | 7.667180 | 7.667180 | 7.667180 |
| Mean    | 7.667180  | 7.667194 | 7.667180 | 7.667180 | 7.667180 | 7.667180 |
| **F2**  | Std 1.78E - 15 | 4.76E - 06 | 1.78E - 15 | 1.78E - 15 | 1.78E - 15 | 1.78E - 15 |
|         | t-test     |        |       |       |       |       |       |
|         | W-test     |        |       |       |       |       |       |
| Best    | 4.579582  | 4.579587 | 4.579636 | 4.580169 | 4.579592 | 4.670711 |
| Mean    | 4.579584  | 4.579597 | 4.613342 | 4.611562 | 4.589737 | 5.017949 |
| **F3**  | Std 1.65E - 06 | 3.02E - 06 | 7.17E - 02 | 5.14E - 02 | 4.27E - 02 | 2.26E - 01 |
|         | t-test     |        |       |       |       |       |       |
|         | W-test     |        |       |       |       |       |       |
| Best    | 2.000000  | 2.000000 | 2.000000 | 2.000000 | 2.000000 | 2.000000 |
| Mean    | 2.000000  | 2.000000 | 2.001420 | 2.000000 | 2.002490 | 2.000000 |
| **F4**  | Std 0.00E + 00 | 2.81E - 07 | 4.44E - 16 | 1.40E - 02 | 4.44E - 16 | 2.35E - 02 |
|         | t-test     |        |       |       |       |       |       |
|         | W-test     |        |       |       |       |       |       |
| Best    | 2.124468  | 2.124470 | 2.124469 | 2.124469 | 2.124469 | 2.124469 |
| Mean    | 2.124488  | 2.124470 | 2.133572 | 2.142858 | 2.124567 | 2.133234 |
| **F5**  | Std 2.03E - 04 | 6.42E - 07 | 6.07E - 02 | 8.48E - 02 | 2.42E - 04 | 6.07E - 02 |
|         | t-test     |        |       |       |       |       |       |
|         | W-test     |        |       |       |       |       |       |
| Best    | 5.25E - 06 | 2.97E - 02 | 6.82E - 02 | 6.54E - 02 | 6.22E - 02 | 3.02E - 02 |
| Mean    | 1.076543  | 1.076546 | 1.102035 | 1.108898 | 1.103897 | 1.077931 |
| **F6**  | Std 5.25E - 06 | 2.97E - 02 | 6.82E - 02 | 6.54E - 02 | 6.22E - 02 | 3.02E - 02 |
|         | t-test     |        |       |       |       |       |       |
|         | W-test     |        |       |       |       |       |       |
| Best    | 99.239640 | 99.239635 | 99.239640 | 99.239640 | 99.239640 | 99.239640 |
| Mean    | 99.239640 | 99.241553 | 102.469891 | 101.291827 | 99.325068 | 99.240113 |
| **F7**  | Std 1.42E - 14 | 1.71E - 03 | 3.91E + 00 | 3.32E + 00 | 8.50E - 01 | 3.47E - 03 |
|         | t-test     |        |       |       |       |       |       |
|         | W-test     |        |       |       |       |       |       |
| Best    | 3.557461  | 3.557466 | 3.558204 | 3.557911 | 3.607595 | 3.570644 |
| Mean    | 3.559827  | 3.559835 | 3.585373 | 3.592501 | 3.607832 | 3.665221 |
| **F8**  | Std 6.56E - 03 | 4.88E - 03 | 3.88E - 02 | 4.15E - 02 | 6.88E - 04 | 6.32E - 02 |
|         | t-test     |        |       |       |       |       |       |
|         | W-test     |        |       |       |       |       |       |
| Best    | -32217.430000 | -32217.42778 | -32217.430000 | -32217.430000 | -32217.430000 | -32217.430000 |
| Mean    | -32217.430000 | -32217.42778 | -32217.430000 | -32217.430000 | -32217.430000 | -32217.430000 |
| **F9**  | Std 3.64E - 12 | 2.19E - 11 | 3.64E - 12 | 3.64E - 12 | 3.64E - 12 | 3.64E - 12 |
|         | t-test     |        |       |       |       |       |       |
|         | W-test     |        |       |       |       |       |       |
| Best    | -0.808844 | -0.808844 | -0.808844 | -0.808844 | -0.808844 | -0.726114 |
| Mean    | -0.808844 | -0.808844 | -0.808844 | -0.808775 | -0.807086 | 0.767928 |
| **F10** | Std 2.22E - 16 | 3.25E - 11 | 2.95E - 03 | 6.84E - 04 | 5.63E - 03 | 1.65E + 00 |
|         | t-test     |        |       |       |       |       |       |
|         | W-test     |        |       |       |       |       |       |
| Best    | -0.974565 | -0.974565 | -0.974565 | -0.974565 | -0.974565 | -0.974565 |
| Mean    | -0.974565 | -0.974565 | -0.974565 | -0.974255 | -0.974565 | 0.961576 |
| **F11** | Std 1.11E - 16 | 1.56E - 15 | 1.11E - 16 | 2.12E - 03 | 1.11E - 16 | 1.27E - 02 |
|         | t-test     |        |       |       |       |       |       |
|         | W-test     |        |       |       |       |       |       |
The best numbers are given in bold, and the lower values of results indicate better optimization ability.

### Table 1: The summary results of the $t$-test and $W$-test on the benchmark functions.

| Fun | Metric | AHcHLO | HcHLO | ASHLO | IAHLO | SFPSO | ALPSO |
|-----|--------|--------|-------|-------|-------|-------|-------|
| Best | $-1.000000$ | $-1.000000$ | $-1.000000$ | $-1.000000$ | $-1.000000$ | $-1.000000$ | $-1.000000$ |
| Mean | $-1.000000$ | $-0.999892$ | $-1.000000$ | $-1.000000$ | $-1.000000$ | $-1.000000$ | $-0.999999$ |
| $F_{12}$ | Std | $0.00E + 00$ | $9.54E - 06$ | $4.01E - 08$ | $1.40E - 08$ | $0.00E + 00$ | $3.22E - 06$ |
| $t$-test | | | | | | | |
| $W$-test | | | | | | | |
| Best | $5850.383000$ | $5850.438514$ | $5850.961000$ | $5850.522000$ | $6090.693000$ | $5903.295000$ | $5939.289830$ |
| Mean | $5974.989830$ | $5980.948418$ | $6010.429390$ | $5980.964330$ | $6104.016650$ | $6347.670080$ | $6326.706830$ |
| $F_{13}$ | Std | $1.08E + 02$ | $1.01E + 02$ | $1.11E + 02$ | $1.21E + 02$ | $4.94E + 01$ | $2.92E + 02$ |
| $t$-test | | | | | | | |
| $W$-test | | | | | | | |
| Best | $-75.134170$ | $-75.134137$ | $-75.132390$ | $-75.133670$ | $-75.133990$ | $-75.131530$ | $-75.131530$ |
| Mean | $-75.134170$ | $-75.134137$ | $-74.880659$ | $-74.919266$ | $-74.958547$ | $-72.689203$ | $-72.708450$ |
| $F_{14}$ | Std | $2.84E - 14$ | $1.11E - 07$ | $8.38E - 02$ | $1.11E - 01$ | $1.37E - 01$ | $2.65E + 00$ |
| $t$-test | | | | | | | |
| $W$-test | | | | | | | |

### 4.2. Segmentation Simulation for Furnace Flame.

The proposed NACMM was adopted to identify the flame images of different combustion states, which was compared with the three recent methods, i.e., statistical color model (SCM) [11], ICA K-medoids-based color model (ICA-KCM) [17], and new conversion-based target-oriented color space model (NCTCSM) [21]. The comparison results of flame segmentation of original images I–XV are displayed in Figure 8, in which Figure 8(a) shows the original flame images I–XV and Figures 8(b)–8(e) indicate the segmentation effects of SCM, ICA-KCM, NCTCSM, and NACMM, respectively. Besides, for quantitative comparison, two evaluation metrics, i.e., detection accuracy (DA) and error rate (ER), were adopted to objectively evaluate the performance of all the methods. DA/ER is the proportion of the number of correctly/wrongly classified pixels (flame and nonflame) to the total number of pixels, respectively. Higher values of DA and
Figure 8: The comparison results of flame segmentation of original images I–XV: (a) original images I–XV; (b) results from SCM; (c) results from ICA-KCM; (d) results from NCTCSM; (e) results from proposed NACMM.
| Original image | Method | False pixels | Correct pixels | ER (%) | DA (%) |
|---------------|--------|--------------|----------------|--------|--------|
| Original image I | SCM | 9325 | 135875 | 6.42 | 93.58 |
| | ICA-KCM | 30541 | 114659 | 21.03 | 78.97 |
| | NCTCSM | 6316 | 138884 | 4.35 | 95.65 |
| | Proposed NACMM | 4137 | 141063 | 2.85 | 97.15 |
| Original image II | SCM | 7800 | 112200 | 6.50 | 93.50 |
| | ICA-KCM | 11021 | 108979 | 9.18 | 90.82 |
| | NCTCSM | 10750 | 109250 | 8.96 | 91.04 |
| | Proposed NACMM | 6004 | 113996 | 5.00 | 95.00 |
| Original image III | SCM | 37648 | 59552 | 38.73 | 61.27 |
| | ICA-KCM | 26367 | 70833 | 27.13 | 72.87 |
| | NCTCSM | 2319 | 74481 | 3.02 | 96.98 |
| | Proposed NACMM | 1545 | 75255 | 2.01 | 97.99 |
| Original image IV | SCM | 28336 | 103964 | 21.42 | 78.58 |
| | ICA-KCM | 2686 | 129614 | 2.03 | 97.97 |
| | NCTCSM | 2538 | 129762 | 1.92 | 98.08 |
| | Proposed NACMM | 2194 | 130106 | 1.66 | 98.34 |
| Original image V | SCM | 7050 | 112950 | 5.88 | 94.13 |
| | ICA-KCM | 2667 | 117333 | 2.22 | 97.78 |
| | NCTCSM | 2495 | 117505 | 2.08 | 97.92 |
| | Proposed NACMM | 1430 | 118570 | 1.19 | 98.81 |
| Original image VI | SCM | 4156 | 115844 | 3.46 | 96.54 |
| | ICA-KCM | 14387 | 105613 | 11.99 | 88.01 |
| | NCTCSM | 1957 | 118043 | 1.63 | 98.37 |
| | Proposed NACMM | 1884 | 118116 | 1.57 | 98.43 |
| Original image VII | SCM | 7371 | 79329 | 8.50 | 91.50 |
| | ICA-KCM | 4135 | 82565 | 4.77 | 95.23 |
| | NCTCSM | 3569 | 83131 | 4.12 | 95.88 |
| | Proposed NACMM | 2488 | 84212 | 2.87 | 97.13 |
| Original image VIII | SCM | 23723 | 134977 | 14.95 | 85.05 |
| | ICA-KCM | 2369 | 156331 | 1.49 | 98.51 |
| | NCTCSM | 2401 | 156299 | 1.51 | 98.49 |
| | Proposed NACMM | 737 | 157963 | 0.46 | 99.54 |
| Original image IX | SCM | 32349 | 140451 | 18.72 | 81.28 |
| | ICA-KCM | 28058 | 144742 | 16.24 | 83.76 |
| | NCTCSM | 21830 | 150970 | 12.63 | 87.37 |
| | Proposed NACMM | 9838 | 162962 | 5.69 | 94.31 |
| Original image X | SCM | 10153 | 66647 | 13.22 | 86.78 |
| | ICA-KCM | 5626 | 71714 | 7.33 | 92.67 |
| | NCTCSM | 3887 | 72913 | 5.06 | 94.94 |
| | Proposed NACMM | 2696 | 74104 | 3.51 | 96.49 |
| Original image XI | SCM | 27593 | 49207 | 35.93 | 64.07 |
| | ICA-KCM | 3579 | 73221 | 4.66 | 95.34 |
| | NCTCSM | 2356 | 74444 | 3.07 | 96.93 |
| | Proposed NACMM | 1630 | 75170 | 2.12 | 97.88 |
| Original image XII | SCM | 11965 | 74735 | 3.80 | 96.20 |
| | ICA-KCM | 5167 | 81533 | 5.96 | 94.04 |
| | NCTCSM | 4446 | 82254 | 5.13 | 94.87 |
| | Proposed NACMM | 2551 | 84149 | 2.94 | 97.06 |
| Original image XIII | SCM | 59654 | 60346 | 49.71 | 50.29 |
| | ICA-KCM | 25457 | 94543 | 21.21 | 78.79 |
| | NCTCSM | 10266 | 109734 | 8.56 | 91.45 |
| | Proposed NACMM | 5325 | 114675 | 4.44 | 95.56 |
lower values of ER indicate better accuracies. The comparison metrics of flame segmentation of original images I–XV are listed in Table 3, where the best results have been marked with boldface.

Figure 8 and Table 3 clearly show that the proposed method can effectively improve the detection accuracy and the segmentation effect of combustion flame. The characteristics of the NACMM as well as the other three recent methods can be concluded as follows:

1. From Figure 8(b), the segmentation effects of original images I, II, III, V, VIII, IX, X, XI, XII, XIII, XIV by using SCM are not ideal, which cannot effectively distinguish flame pixels and nonflame pixels. In particular, for the original images III, V, IX, X, XI, XII, XIII, XIV, the segmentation effect is poor and the numerical values of ER are large. Table 3 shows that the DAs of original images I–XV by using SCM are quite different and the numerical values of DA are 93.58%, 93.50%, 61.27%, 96.33%, 78.58%, 94.13%, 96.54%, 91.50%, 85.05%, 81.28%, 86.78%, 64.07%, 86.2%, 50.29%, and 87.75%, respectively, which points out that SCM cannot segment the flame image of different combustion status.

2. Figure 8(c) shows that the ICA-KCM has the same disadvantages of SCM, which cannot effectively segment the flame image of different combustion status, in which the segmentation effects of original images I, II, III, VII, X, XI, XIV by using ICA-KCM are also not ideal.

3. Figure 8(d) indicates that the segmentation effect and the detection accuracy of NCTCSM are better than those of SCM and ICA-KCM because it uses the PSO algorithm to optimize the color space model with nine variables, which can segment the flame pixels of different combustion states. However, this recognition model is relatively complicated; it is difficult to obtain a high-precision recognition model, which causes the values of DA of NCTCSM to be lower than those of NACMM.

4. Figure 8(e) points out that the proposed NACMM can effectively identify the flame image of different combustion statuses, which obtains the best segmentation effect and the highest detection accuracy of combustion flame. Specifically, the DA of original images I–XV are 97.15%, 95.00%, 93.94%, 97.99%, 98.34%, 98.81%, 98.43%, 97.13%, 99.54%, 94.31%, 96.49%, 97.88%, 97.06%, 95.56%, and 91.77%, respectively, which are better than those of SCM, ICA-KCM, and NCTCSM. The numerical values of DA for fifteen combustion flame images I–XV are greater than 90%, which proves that the proposed NACMM has good robustness. Besides, the results of the average values of ER and DA also demonstrate the superiority of NACMM, which obtains the best numerical results; that is, the values of ER and DA are 3.25% and 96.75%, respectively.

In conclusion, the segmentation effects of both SCM and ICA-KCM are not ideal because they do not have the objective function to adapt to different combustion states, and it is difficult for the NCTCSM to obtain a high-precision segmentation model because the optimized model parameters are complicated. Compared with SCM, ICA-KCM, and NCTCSM, the proposed NACMM can segment the flame image of different combustion statuses more effectively and accurately, which can obtain an ideal adaptive segmentation model for adapting to different combustion states.

5. Conclusions and Future Work

Designing and developing high detection accuracy technology for flame segmentation are crucial, which can effectively help operators adjust combustion strategies for improving combustion utilization. However, the combustion states, as well as the RGB components of combustion flame, inside the industrial furnace change according to the production needs, which is not considered in the previous works and further challenges the optimal set of model parameters. Therefore, a novel segmentation method for furnace flame using adaptive color model and hybrid-coded HLO is proposed to segment the flame pixels more accurately and effectively, in which the NACMM is designed for adapting to the flame image of different combustion states. As the objective function of NACMM is a hybrid-coding problem, the AHcHLO is developed to solve the optimized parameters of NACMM. Regarding this proposed NACMM, two objective functions are adopted as the evaluation index to evaluate the segmentation accuracy and reduce the structural risk. Firstly, AHcHLO is applied to solve the benchmark functions for evaluating its optimization ability.
and the numerical results show that AHcHLO possesses the best-known overall results so far on these benchmark functions, which further ensures the parameter optimization of NACMM for guaranteeing the best effect. Then, the segmentation simulation demonstrates that the proposed NACMM outperforms state-of-the-art flame segmentation approaches in detection accuracy and segmentation effect for different combustion states.

The color model is extremely important for the segmentation effect of flame image, and the hue and saturation can also influence the segmentation effect of flame image. Therefore, the following research will focus on studying the advanced yet complicated color model with mixed variables to further improve the detection accuracy of combustion flame. However, considering that this color model contains more variables, it needs a more powerful HLO algorithm to obtain the best color model, which will be challenging for future work.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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