Assessment of human operator functional state using a novel differential evolution optimization based adaptive fuzzy model

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ABSTRACT

With the development of human–machine systems, there has been a growing concern about the consequences of operator performance breakdown under excessive level of workload, especially in safety-critical situations. Assessment and detection of the operator functional state (OFS) enable us to predict the high operational risks of operator. This paper adopts the psychophysiological signals and task performance measures to evaluate OFS under different levels of mental workload. Four indices extracted from electrocardiogram and electroencephalogram, including heart rate (HR), ratio of the standard deviation to the average of HR segment, task load indices (TLI1 and TLI2), are chosen as the inputs of the proposed model. A technique of differential evolution with ant colony search (DEACS) is developed to optimize the parameters of Adaptive-Network-based Fuzzy Inference System (ANFIS). The optimized ANFIS model is employed to estimate the OFS under a series of process control tasks on a simulated software platform of AUTOmation-enhanced Cabin Air Management System. The results showed that the proposed adaptive fuzzy model based on ANFIS and DEACS algorithm is applicable for the operator functional state assessment.

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1. Introduction

During the modern development of automation technique, highly automated systems require few manual activities for individuals to perform. Human becomes the monitor and decision maker in the automatic system. Consequently, it brings more information processing loads and broader ranges of responsibilities to individuals. Therefore, the increased responsibility and decision making authority to each individual probably cause that the human operators become the weakest links in the operational loop [1–3]. The operator’s performance degradation (because of vigilance decrease, fatigue, inattentiveness, sleepiness, pain, etc.) was the reason of some serious disasters [4]. To reduce this kind of disasters, researchers have begun to turn attention to the study of the performance of operators, particularly in safety-critical applications such as public transportation (railway [5], aviation [6,7], driving [8]) and manufacturing industries (chemical [9] and nuclear plants [10]).

Adaptive automation has been proposed to solve the above problem. In adaptive automation, the control tasks can be reallocated dynamically between operators and automatic systems according to the operators’ performance level and whole system operation requirements. For example, when high operator mental workload is detected, some of the manual control tasks may be taken away and switched to the automatic system. On the other hand, high level of automation continuing for long time would result in lack of concentration for the operator. Proper manual control tasks should be reallocated to the operator.

There are three primary approaches to generate criteria for task reallocation [1]: (a) critical events logic where automation is engaged consistently in response to an environmental stimulus; (b) model-based approaches where automation is ‘scheduled’ based on a priori models of optimal operator performance; and (c) continuous assessment of operator function and mental state. For the third approach, continuous operator functional state (OFS) assessment is usually achieved through the following ways: (1) subjective assessments of the operator’s mental workload; (2) performance of the operator on the primary task, and sometimes secondary tasks; (3) psychophysiological measurements of the operator. The authors’ current work is to investigate accurate and reliable assessment of OFS by psychophysiological measurements.

The psychophysiological signals, including electrocardiogram (ECG), electroencephalogram (EEG), eye blink, respiration, blood pressure, electrodermal activity, etc., have been demonstrated to be sensitive to the changes in OFS. Among those signals, the indices from ECG and EEG have been commonly used to assess the mental workload.

Heart rate (HR) and heart rate variability (HRV) are efficient indices of mental workload [11–14]. In the previous works of ECG
When high search to settings significant neither tor. of proposed [20]. The task load index (TLI) [21], i.e. ratio of theta to alpha power from different sites, is selected for OFS assessment. In this study, HR, HRV1, and TLI (TLI1 and TLI2) are chosen as the inputs to the proposed model for OFS assessment.

Several studies have been done on the psychophysical signals and artificial neural networks (ANNs) to classify the levels of OFS [21–23]. Wilson and Russell [24] reported high accuracy of OFS classification using ANNs, i.e. 85%, 82%, and 86% for baseline, low and high task difficulty conditions, respectively. However, due to the characteristics of ANNs (the implicit knowledge representation), the relationship between input features and OFS was not explained.

Adaptive-Neural-based Fuzzy Inference System (ANFIS) with the explicit knowledge representation was employed to estimate OFS [25,26]. ANFIS can simulate and analyze the mapping relation between the input and the output data by a learning algorithm to optimize its parameters. It is widely used to build complex and nonlinear relationship between a set of input and output data [27,28]. In [25], basic ANFIS was used for OFS assessment. The premise parameters and consequent parameters of ANFIS were identified by gradient descent method and least squares estimation, respectively [29]. The results showed that the generalization capability of ANFIS was not satisfied. Because of over-fitting, the basic ANFIS model output is not reliable in real application.

In this paper, a differential evolution algorithm with ant colony search (DEACS) is proposed to optimize the parameters of ANFIS. Differential evolution (DE) [30,31] is a population-based stochastic optimization algorithm, which has the capability of global optimization and quick convergence. In DE algorithm, there are two significant control parameters: mutation factor and crossover factor. The two factors determine whether DE algorithm can find a good optimal solution. In the original DE algorithm, some recommended settings of the two factors were given through many optimization experiments for test functions. These are empirical settings from statistical results, and would be constant at different stages of evolution. To improve the performance of DE, some researchers developed new strategies to adjust the two factors by linear variation [32] and random selection [33,34], etc. However, neither linear variation nor random selection is related to the evolution state. Therefore, the idea of ant colony search is employed to find out the proper combination of mutation and crossover factors adaptive to each individual according to current optimization performance. ACS [35] simulates the behavior of ant colony system. When ants prefer in probability to one path (i.e. a combination of mutation and crossover factors) since there are a greater quantity of pheromone on this path, the quantity of pheromone would be further increased. The positive feedback effect of ACS is applicable to selecting the combination of the factors as the most appropriate choice for DE. Instead of being constant or varying by some specific rules, the two factors can be determined adaptively. Applying ACS avoids the inefficiency which results from the improper selection of the two factors. The developed DEACS–ANFIS model is established to assess OFS. The obtained results are compared with ANFIS and DE based ANFIS (DE–ANFIS).

The rest of the paper is arranged as follows. In Section 2, the data acquisition experiment is described in details. Section 3 presents the ANFIS and DEACS algorithm, respectively, and establishes an adaptive fuzzy model based on DEACS–ANFIS for OFS assessment. In Section 4, the experimental results are illustrated, and the discussions are presented. Section 5 includes the conclusions and future works.

2. Experiment

2.1. Data acquisition equipment

The experiments were carried out on AUTomation-enhanced Cabin Air Management System (AUTOCAMS), which was developed by Hockey et al. [36] and modified by Lorenz and Parasuraman [37]. AUTOCAMS simulates a life support system of a spacecraft. It requires the subject (operator) to manage a semi-automatic system which is to regulate atmospheric conditions of the cabin so as to maintain comfortable atmospheric condition. There are five sub-systems (Fig. 1) corresponding to five critical parameters of atmospheric condition (oxygen concentration, carbon dioxide concentration, temperature, pressure, humidity). The subject was instructed to control some of the sub-systems manually according to the experimental design.

2.2. Participants

Before data acquisition experiment, subjects with an engineering background were trained by the manual process control tasks for over 10 h and a further 12–15 h experience of controlling the system under a range of conditions. After the training, they would become expert users of AUTOCAMS. Finally, there are totally 10 healthy male subjects selected to participate in the experiments.

2.3. Experimental procedure

Every subject was required to work for two sessions at the same time on different days to avoid circadian effect. Each session consists of 9 control conditions. Each control condition is lasted for 15 min. The primary task of the subject was defined to control some of the five subsystems so as to maintain their relevant variables within target ranges. The number of subsystems that needed to be controlled manually under each control condition is 1, 2, 3, 4, 5, 4, 3, 2, and 1, respectively. Therefore, the task load would vary during the experiment. In addition, there were two secondary tasks: alarm acknowledgement and tank level record. Alarm acknowledgement required the subject to click the mouse as soon as possible when he heard the alarm. Tank level record required the subject to record
the current oxygen tank level per minute. At the end of each control condition, subjective state measurements on anxiety, effort and fatigue were made by onscreen visual analogue scales.

2.4. Data acquisition and processing

The Active Two Base System (Biosemi, The Netherlands) was used for continuously acquiring psychophysiological signals: ECG, EEG (32 sites on a head-cap arranged in 10–20 system with FC5, T7, T8, FC6 replaced by FPz, AFz, CPz, POz, respectively), reference (left and right mastoids).

HR was calculated using the LabVIEW virtual instruments. HRV1 is defined as the HR variation coefficient as the following expression:

\[
\text{HRV1} = \frac{\sigma_{\text{HRV}}}{\mu_{\text{HRV}}} \quad (1)
\]

where \(\sigma_{\text{HRV}}\) and \(\mu_{\text{HRV}}\) denote the standard deviation and the average of HRV segment of every 2 min.

The EEG data were sampled at 2048 Hz and passed by a band-pass filter between 1.6 and 55 Hz. The eye movements and baseline changes were corrected. The continuous EEG data was segmented into epochs of 2 s. And then the segmented data were analyzed by Fast Fourier Transform. The power of different frequency bands was calculated. Two types of TIR, which are known to reflect changes in operator’s effort and attention on current task, are calculated by the following equation:

\[
\begin{align*}
\text{TIR1} &= \frac{P_{\theta,Fz}}{P_{\theta,FPz}}, \\
\text{TIR2} &= \frac{P_{\theta, AFz}}{P_{\theta, CPz} + P_{\theta, POz}},
\end{align*}
\quad (2)
\]

where \(P_{\theta}\) and \(P_{\alpha}\) denote the theta and alpha band power, respectively. The frequency bands are defined in the following: \(\theta, \text{Fz}: \) 6–7 Hz; \(\alpha, \text{Fz}: \) 10–12 Hz; \(\theta, \alpha, \text{AFz}: \) 5–7 Hz; \(\alpha, \text{CPz}: \) 8–10 Hz; \(\alpha, \text{POz}: \) 10–13.5 Hz.

System performance parameters were sampled at 1 Hz and recorded on the process control computer. The thresholds of subsystem variables were defined, out of which “system in error (SIE)” was detected. Time in range (TIR) is defined as the percentage of the time when subsystem variables are within the thresholds. TIR was calculated for every 2 min as the following equation.

\[
\text{TIR} = \frac{\text{SIE}}{2 \times 60} \times 100\%.
\]

As the primary task performance, TIR is regarded as the most direct prediction of OFS. In this paper, TIR is assumed to reflect OFS completely, e.g. low TIR indicates high operator mental workload. It is a measurement variable as the output of OFS model.

3. ANFIS based on differential evolution with ant colony search

In this section, an adaptive fuzzy model is proposed. ANFIS is utilized to build the structure of the proposed model. An improved differential evolution with ant colony search is adopted to optimize the parameters of ANFIS.

3.1. ANFIS architecture

ANFIS [29,38] results from the integration of neural network and fuzzy inference system (FIS). In ANFIS, Takagi–Sugeno (TSK) type fuzzy rule processing techniques are used to generate the fuzzy rules.

For an adaptive fuzzy inference system with two inputs \(I_{n1}, I_{n2}\) and one output \(z\), assume that the rule base contains two if–then rules of TSK type:

\[
\text{Rule 1: If } I_{n1} = A_1 \text{ and } I_{n2} = B_1, \text{ then } f_1 = p_1 I_{n1} + q_1 I_{n2} + s_1,
\]

\[
\text{Rule 2: If } I_{n1} = A_2 \text{ and } I_{n2} = B_2, \text{ then } f_2 = p_2 I_{n1} + q_2 I_{n2} + s_2.
\]

The corresponding equivalent ANFIS (type-3 ANFIS) architecture is shown in Fig. 2. It is a five-layer network which is described as below.

Layer 1: Every node \(I\) is adaptive with a node function:

\[
O_I^1 = \mu_{A_i}(I_{n1}), \quad I = 1, 2.
\]

where \(I_{n1}\) is the input to node \(I, A_i\) is the linguistic label associated with this node function and \(\mu_{A_i}(I_{n1})\) is the fuzzy membership function of \(A_i, \mu_{A_i}(I_{n1})\) is described by Gaussian function.

\[
\mu_{A_i}(I_{n1}) = \exp\left(\frac{-(I_{n1} - c_i)^2}{2\sigma_i^2}\right),
\]

where \((\sigma_i, c_i)\) is the premise parameter set.

Layer 2: The node function is given by,

\[
O_{wI}^2 = w_I = \mu_{A_i}(I_{n1}) \times \mu_{B_i}(I_{n2}), \quad I = 1, 2.
\]

Layer 3: Each node \(I\) calculates the normalized firing strength and is represented as,

\[
O_I^3 = \frac{W_I}{W_1 + W_2}, \quad I = 1, 2.
\]

Layer 4: Every node is an adaptive node with a node function given by,

\[
O_I^4 = \frac{W_{fI}}{W_{lI}} = \frac{W_I}{W_I + q_I I_{n1} + s_I}, \quad I = 1, 2,
\]

where \((p_I, q_I, s_I)\) is the consequent parameter set.

Layer 5: In this layer, the overall output is calculated as,

\[
O_5^5 = \sum_i W_I^f = \sum_i W_I f_I, \quad I = 1, 2.
\]

In the ANFIS architecture, there are two types of adaptive parameters, i.e. premise parameters \((\sigma_i, c_i)\) and consequent parameters \((p_I, q_I, s_I)\). Those parameters are related to the fuzzy membership functions and the first-order polynomial, respectively.

3.2. Differential evolution with ant colony search (DEACS)

Differential evolution is a population-based heuristic optimization algorithm. Assume that \(\text{Popsize}\) individuals are contained in the population. For a \(D\)-dimensional problem space, each individual \(x^i, i = 1, 2, \ldots, \text{Popsize}\) at \(t\)th generation is represented as a candidate solution. The initial population is distributed uniformly in the search region. Then DE algorithm is performed by mutation, crossover, and selection operations.
Mutation operation:

\[ u_i^t = x_i^t + F \cdot (x_i^t - x_r^t), \]  

where \( u_i^t \) is the mutant individual for \( x_i^t, r_1, r_2, r_3 \) are random indices of individuals and different from each other. Moreover, they are not equal to \( t \). \( F \) is mutation factor in the range of \([0,1]\).

Crossover operation:

\[ y_{id}^t = \begin{cases} 
  u_{id}^t & \text{if } \text{rand} \leq C_R, \\
  x_{id}^t & \text{otherwise},
\end{cases} \]

where \( y_{id}^t \) is the trial individual, \( d \) represents the \( d \)th component of individuals, and \( \text{rand} \) is a uniformly distributed random number in \([0,1]\). The crossover factor \( C_R \) is a parameter in \([0,1]\).

Selection operation: After all \( \text{Popsize} \) trial individuals are generated, the selection operation is processed.

\[ x_i^{t+1} = \begin{cases} 
  y_i^t & \text{if } \text{fitness}(y_i^t) \leq \text{fitness}(x_i^t), \\
  x_i^t & \text{otherwise},
\end{cases} \]

where \( \text{fitness}(\cdot) \) is the fitness function.

As the above description, there are two tuning factors, \( F \) and \( C_R \), which greatly affect the balance between exploration and exploitation ability of DE. \( F \) is used to control the amplification of the differential variation. The crossover factor \( C_R \) expresses the possibility with which the crossover operation happens. In the existing works, \( F \) and \( C_R \) are set by the user in advance or vary by some specific rules. However, it is very difficult to choose the factors due to the lack of prior knowledge. Here, the idea of ant colony search is considered to self-adaptively find the proper combination of \( F \) and \( C_R \) so as to accelerate the global convergence.

In DEACs, \( F \) and \( C_R \) can be set in the range of \([0,1]\). We use 10 values here, i.e., \( F \in \{0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0\} \) and \( C_R \in \{0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0\} \). Of course, it can be extended to different sets of values. At every generation, the individuals are regarded as ants. Each of the ants selects a combination of \( F \) and \( C_R \) according to a heuristic information and pheromone information. The information collected by the ants during the search process is stored in pheromone trails. The ants cooperate in choosing different but most appropriate combination of \( F \) and \( C_R \) by exchanging information via the pheromone trails. The ant colony system updates the pheromone trails based on the performance of all the ants.

The pheromone trail \( \tau_{mn} \), associated with choosing \( n \)th value \((n = 1, 2, \ldots, 10)\) as the setting of \( m \)th parameter \((m = 1, 2; 1\)st parameter represents \( F \); 2nd represents \( C_R \)), is updated by

\[ \tau_{mn}(t + 1) = (1 - \rho) \tau_{mn}(t) + \sum_{i=1}^{\text{Popsize}} \Delta \tau_{mn}^i(t), \]

where \( 0 < \rho < 1 \) is the pheromone trail evaporation rate, \( \Delta \tau_{mn}^i(t) \) is the quantity of pheromone related to the performance of ant \( i \) as

\[ \Delta \tau_{mn}^i(t) = \begin{cases} 
  1.0 & \text{if } i \in X_{mn} \text{ and } \text{fitness}(y_i^t) < \text{fitness}(x_{best}^t), \\
  0.5 & \text{if } i \in X_{mn} \text{ and } \text{fitness}(x_{best}^t) < \text{fitness}(y_i^t) \text{ and } \text{fitness}(y_i^t) < \text{fitness}(x_i^t), \\
  0 & \text{otherwise},
\end{cases} \]

where \( X_{mn} \) is the set of the ants which choose \( n \)th value as the setting of \( m \)th parameter, and \( x_{best}^t \) is the best ant in the ant colony till \( t \)th generation.

The probability with which each ant chooses \( n \)th value as the setting of \( m \)th parameter is given by,

\[ p_{mn}(t) = \begin{cases} 
  \frac{\tau_{mn}(t)}{\sum_{i=1}^{\text{Popsize}} \tau_{mn}(t)} & \text{if } \text{rand}_1 < p_i, \\
  \text{rand}_2 & \text{otherwise},
\end{cases} \]

where \( \text{rand}_1 \) and \( \text{rand}_2 \) are two uniformly distributed random numbers in the range of \([0,1]\), and \( p_i \) is a selection rate with which the ant uses \( \tau_{mn}(t) \), to choose the best path. The objective of introducing this operation is to prevent the ants from being limited to only one ant path so as to increase the probability of choosing other paths.

Fig. 3 illustrates the relationship between ant paths, pheromone matrix and \( F \), \( C_R \). For example, starting from the initial state, an ant moves through the ant path marked by the red dot dash lines. The nodes visited by the ant are selected as the values of \( F \) and \( C_R \), respectively. Selection of the values depends on the pheromone trails on the path. At each generation, the most appropriate combination of \( F \) and \( C_R \) for each individual is chosen based on the performance of the whole population. It enables the individuals to converge globally and fast.

### 3.3. OFS assessment based on ANFIS and DEACs

ANFIS has already been used to estimate OFS due to its features of nonlinear mapping and distributed processing. How to choose the adaptive parameters of ANFIS is an important issue because it directly influences the generalization accuracy. In this study, the proposed DEACs algorithm is used to optimize the parameters of ANFIS.

The number of adaptive parameters is determined by the number of inputs and membership function parameters and fuzzy partitions,

\[ N_{\text{Para}} = N_{\text{Pru}} + N_{\text{Con}} = N_{\text{In}} \times N_{\text{MF}} \times N_{\text{FP}} + (N_{\text{In}} + 1) \times N_{\text{FP}} N_{\text{In}}, \]

where \( N_{\text{Pru}}, N_{\text{Pre}}, N_{\text{Con}} \) denote the number of the adaptive parameters, premise parameters and consequent parameters, respectively; \( N_{\text{In}}, N_{\text{MF}}, N_{\text{FP}} \) represent the number of inputs, membership function parameters and fuzzy partitions, respectively. In Eq. (16), it can be
4. Experimental results and discussion

4.1. Training and checking data

The DEACS based ANFIS model (DEACS–ANFIS) is used for OFS assessment. The inputs of the model include HR, HRV1, TLI1 and TLI2, which were found to be most sensitive to the changes of OFS [15,16,39]. TIR is selected to be the output.

Different from the works [25,26] using 7.5 min, the sampling interval of inputs and output data is set to 2 min. The modified sampling interval allows more data information for analysis and facilitates the real-time assessment of OFS. However, it increased the difficulty for accurate assessment of OFS. At the beginning of each control condition, the level of automation was reset. At the end of each control condition, the operator was required to take a subjective record about the fatigue, anxiety and effort. Therefore, 30 s of data at the beginning and end of each condition were eliminated. Totally, we collected 63 samples (14 min/2 min × 9 control conditions) of psychophysiological and task performance data in each session (126 samples totally for one subject). The input and output data measured from two experimental sessions for subject P01 are shown in Fig. 5.

The samples, which are constructed by HR, HRV1, TLI1, TLI2, and TIR, were divided into training and checking data. The samples measured from sessions 1 and 2 were concatenated together. Two thirds of the samples ([j3 + 1]th,(j3 + 2)th points of the concatenated data, j = 0, 1, 2,...) were chosen as training data. All the samples were checking data. Therefore, the data information from both of the sessions was utilized in the training process. All the data were normalized into the range of [−1,1].

4.2. Initial DEACS–ANFIS structure

Fig. 6 shows the initial membership functions. The consequent parameters \( \{ s_i \} \) were initialized randomly in [−5,5].

The parameter settings of DEACS are given as follows: the maximum generation MaxGen = 200; Popsie = 50; \( p_i = 0.5 \); \( \rho = 0.1 \).

4.3. Optimization function

The optimization function to be minimized is root mean square error (RMSE), defined by the following equation.

\[
RMSE = \sqrt{\frac{\sum_{k=1}^{N}[z(k) - z_{m}(k)]^2}{N}}
\]

where \( z(k) \) is the kth actual TIR, \( z_{m}(k) \) is the model output TIR at the kth sampling point, N is the amount of samples.

4.4. Results and discussion

Fig. 7 illustrates the optimized membership functions of subject P01 after training ANFIS by using DEACS algorithm. There are 81 (3³) fuzzy rules in the initial DEACS–ANFIS model. After the proposed optimization procedure, some of the fuzzy rules are thought to be redundant for the existing sampling data because their firing strengths are approximately equal to zero (<0.001). For subject P01, there are 56 useful fuzzy rules and 12 of them are shown in Table 1. The “L”, “M” and “H” denote low, medium, and high, respectively. Each row represents a fuzzy rule as,
Rule 1: If (HR is L) and (HRV1 is L) and (TLI1 is L) and (TLI2 is L), then \( f_1 = s_1 = 4.756 \).

According to Eqs. (17) and (9), the output TIR is calculated as below:

\[
\text{TIR} = \sum_{i=1}^{81} \overline{w_{ij}} f_i
\]

(20)

where \( \overline{w_{ij}} \) is the normalized firing strength of the \( i \)th rule, and \( f_i \) is equal to \( s_i \).

The plot of experimental and estimated TIR obtained by using DEACS–ANFIS on both training and checking data for subject P01 is shown in Fig. 8(a) and (b). Fig. 8(c) illustrates the number of subsystems under manual control on each control condition. The results indicate that the DEACS–ANFIS outputs are nearly fitted to the trend of real values. The deviation between the model outputs and real values is acceptable.

The same procedures were performed for the other 9 subjects. The mean absolute errors (MAE) by using DEACS–ANFIS for all subjects are shown in Table 2. The accuracy of DEACS–ANFIS model for each subject is different because of individual differences. The low MAE on the checking data may be considered as a good generalization performance.

In a separate study, the same sampling data were exposed to basic ANFIS and DE based ANFIS (DE-ANFIS). Basic ANFIS employs

<table>
<thead>
<tr>
<th>Rule no.</th>
<th>Model inputs</th>
<th>( s_i )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>L L L L</td>
<td>4.756</td>
</tr>
<tr>
<td>2</td>
<td>L L L M</td>
<td>-2.851</td>
</tr>
<tr>
<td>3</td>
<td>L L H M</td>
<td>-3.946</td>
</tr>
<tr>
<td>4</td>
<td>M L M L</td>
<td>3.045</td>
</tr>
<tr>
<td>5</td>
<td>M L M M</td>
<td>-1.706</td>
</tr>
<tr>
<td>6</td>
<td>M M H L</td>
<td>1.026</td>
</tr>
<tr>
<td>7</td>
<td>M H H L</td>
<td>2.639</td>
</tr>
<tr>
<td>8</td>
<td>M H H M</td>
<td>3.957</td>
</tr>
<tr>
<td>9</td>
<td>H L M L</td>
<td>3.129</td>
</tr>
<tr>
<td>10</td>
<td>H H H M</td>
<td>-4.263</td>
</tr>
<tr>
<td>11</td>
<td>H H H M</td>
<td>1.781</td>
</tr>
<tr>
<td>12</td>
<td>H H H M</td>
<td>-2.362</td>
</tr>
</tbody>
</table>
the gradient decent method and least square estimation for identifying the parameters while DE-ANFIS uses basic DE algorithm. The parameters of DE are set as follows: the maximum generation is 200; the population size is 50; \( F = 0.7 \) and \( C_r = 0.5 \). The MAEs by using ANFIS and DE-ANFIS are also summarized in Table 2. The last row of Table 2 presents the average MAEs of all subjects. For the training data, the OFS is successfully estimated by using ANFIS model. However, the model is not reliable for the checking data. The reason is that the over-fitting exists in ANFIS model and results in poor generalization capability. Generally, the generalization capability is the primary concern. From Table 2, it is clear that the checking error of TIR by using DEACS–ANFIS is reduced when comparing with the error by using ANFIS and DE-ANFIS. The average checking MAE of DEACS–ANFIS is 7.42 while 10.464 and 235.0 for DE-ANFIS and ANFIS, respectively. Besides, the one-way analysis for variance (ANOVA) was used to analyze the performance differences between methods. For training data, the accuracy of DEACS–ANFIS is significantly higher than that of DE-ANFIS (\( F(1,18) = 11.81, p < 0.005 \)). For checking data, DEACS–ANFIS yield significant higher accuracy than ANFIS (\( F(1,18) = 54.54, p < 0.000001 \)) and DE-ANFIS (\( F(1,18) = 4.45, p < 0.05 \)). It is concluded that the generalization capability of DEACS–ANFIS model is better than other two modeling methods.

Fig. 7. Final membership functions of all the input variables (P01): the black dotted line, blue dot dash line, and red solid line represent the final MF1, MF2 and MF3, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

Fig. 9 illustrates the convergence process of DE and DEACS in optimizing the parameters of ANFIS. In DEACS, appropriate mutation and crossover factors are selected adaptively according to current optimization performance for each subject. Although the proposed DEACS makes the system a little more complicated (the average training time increases from 31 s to 54 s), it converges to a good solution at about 100th generation. The convergence speed is much more rapid than DE. Moreover, DEACS has the potential to reach better solutions.

The employment of DEACS enables the user to choose the optimum ANFIS parameters with a good accuracy. The experimental results indicate that DEACS–ANFIS has a good generalization performance and is applicable to assessing the mental load status of operators.

In the experiment, some outcomes are not good enough. That is because the relationship between psychophysiological signals and mental work load is not very clear yet. Researchers [40,41] have done many works to analyze the variation of operator’s psychophysiological signals on different mental workloads. The efficiency of psychophysiological signals varies in different experiments. The individual differences are another affected reason. Furthermore, TIR is thought to be the representation of OFS here.

Table 2
Mean absolute error on training and checking data.

<table>
<thead>
<tr>
<th>Subject</th>
<th>ANFIS [25]</th>
<th>DE-ANFIS</th>
<th>DEACS–ANFIS</th>
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<td>Checking</td>
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<tr>
<td>Average</td>
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e.g. high TIR means low mental workload. However, low TIR value also could be seen sometimes when the operator is at low mental workload (Fig. 8).

5. Conclusions

An adaptive fuzzy model, which is called DEACS-ANFIS, was proposed for operator functional state (OFS) assessment. Four psychophysiological signals, including heart rate (HR), heart rate variability (HRV1), task load indices (TLI1 and TLI2), were selected to be the inputs to the proposed model, and time in range (TIR) was the output. The ANFIS architecture provided a transparent assessment of OFS, and helped to easily understand the relationship between psychophysiological signals and OFS. The idea of ant colony search was introduced into differential evolution algorithm for adaptively selecting the appropriate values of mutation and crossover factors. Optimized membership functions in ANFIS architecture were acquired by using DEACS algorithm. The experimental results illustrated that the DEACS–ANFIS based adaptive model is a competitive method to provide the assessment and detection of operator functional state.

As the aforementioned descriptions, future works will focus on two areas to get better models of OFS. More experiments and further analysis on psychophysiological signals will be helpful to obtain general model inputs and reduce the influence of individual differences. Other performance measurements of the operator such as alarm reaction time and subjective performance measurements will be integrated to obtain better representation of OFS.

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References
