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An Optimizing Pulse Coupled Neural Network based on Golden Eagle Optimizer for Automatic Image Segmentation

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Abstract. *An optimizing pulse coupled neural network (PCNN) parameters based on the Golden eagle optimizer (GEO) is suggested in this paper for automatic image segmentation. The optimized parameters would assist in reducing the difficulty of establishing PCNN parameters as lowered while the segmentation impact remains unchanged. The traditional methods for the optimal PCNN parameters would encounter computational complexity time as exponential complexity. The swarm intelligence optimization algorithm is one of the most promising effective ways of dealing with the computational exponential complexity time issues. GEO is a recent robust swarm intelligence optimization algorithm that has advantages as a few parameters, easy implementation, and powerful search capability. The fitness function is figured out as image entropy, and selected brain MRI images are used to verify the proposed scheme for the experiment. The obtained result of the GEO method integrated with PCNN compared to the other optimization techniques shows that the proposed method has a higher segmentation accuracy and resilience and a higher technical application value.*

Keywords: Golden Eagle Optimizer; Image segmentation; Pulse coupled neural network; Entropy; Parameter adaptation; Intelligent optimization algorithm; Neural network.

1. **Introduction.** Image segmentation technology has been widely applied in medical image segmentation [1][2]. The image segmentation can be realized by taking the segmented image's entropy as the condition of implementation in automation that is much-paid attention from scholars [3][4]. Pulse coupled neural network (PCNN) is one of the excellent performances in image processing as the new generation neural network and is widely used in image segmentation [5]. Several works in the kinds of literature are reviewed as following mentioned examples. The application of the saliency algorithm is combined with an improved region growing pulse coupled neural network developed for image segmentation [6]. The PCNN model is simplified with set some parameters adaptively would improve the algorithm performance in classification [5][6]. The mulberry image was processed to obtain the visual saliency map, and then the image was segmented with PCNN [7]. The error back-propagation learning criterion was added to the PCNN model, which reduced the sensitivity of the original model to brightness and contrast [8]. Although the scholars mentioned above have improved PCNN to varying degrees, the setting of PCNN parameters always depends on the manual, and there is no automatic setting [6].

Therefore, many scholars have studied the adaptive set of PCNN parameters [9]. The ant colony algorithm was used to find optimized PCNN parameters and realized brain image segmentation [10]. A variety of intelligent optimization algorithms to optimize the maximum inter-class variance, and then combined with PCNN, was used to segment the image [11]. The particle swarm optimization algorithm (PSO) optimized the parameters of PCNN and proposed an improved comprehensive evaluation index [12]. The genetics optimization algorithm (GA) was used to find an optimized PCNN for segmentation [13]. The sine cosine algorithm (SCA) was to optimize PCNN parameters was proposed [14] and achieved good results. The grey wofl optimization (GWO) combined with PCNN was applied to medical image segmentation, and the brain contour was well segmented [15]. The traditional methods for the optimal PCNN parameters would encounter computational complexity time as exponential complexity [6]. The swarm intelligence optimization algorithm is one of the most promising effective ways of dealing with the computational exponential complexity time issues [16][17]. The Golden eagle optimizer (GEO) [18] is a recent robust swarm intelligence optimization algorithm that has advantages as a few parameters, easy implementation, and powerful search capability. This paper suggests a finding approach to the optimal parameters of PCNN based on the GEO for image segmentation. The optimal parameters of each image in PCNN are figured out by applying GEO that can achieve the optimal image segmentation. The GEO employs the modeled objective function with brain MRI image entropy that seeks the PCNN to reduce the difficulty of establishing parameters for pulse-coupled neural networks. According to the simulation results, the proposed method has a higher segmentation accuracy and resilience and a higher technical application value.

2. **Golden Eagle Optimizer Approach.** The golden eagle optimizer (GEO) is a recently released swarm intelligent algorithm inspired by the golden eagle and the target prey with essential groups [18]. The golden eagle individual represents the candidate solution of the optimization problem. The prey is the target around the golden eagle, who chooses to cruise until the number of iterations. The prey can be used as a "weathervane" for the golden eagle to proceed in the feasible search space. Each golden eagle cruises around a prey. In the early iteration phase, when the cruising intention is more substantial when a better solution is found, it updates its memory of the optimal prey. Over the iteration, the attack tendency of the golden eagle is stronger [18]. Compute the golden eagle's current attack vector is expressed as follows.

$$\overrightarrow{A_i} = \overrightarrow{X_f^*} - \overrightarrow{X_i}, \tag{1}$$

where $\overrightarrow{A_i}$ is the attack vector of $i-th$ golden eagle, $\overrightarrow{X_f^*}$ is the best location (prey) golden eagle f has ever visited. $\overrightarrow{X_i}$ Is the current location of $i-th$ golden eagle. Calculating the cruise vector is tangent hyper-plane calculation that is the scalar form in n-dimensional space.

$$h_1x_1 + h_2x_2 + ... + h_nx_n = d = \sum_{j=1}^{n} h_jx_j \tag{2}$$

where $\overrightarrow{H} = [h_1, h_2, \ldots, h_n]$ is the normal vector; $\overrightarrow{X} = [x_1, x_2, \ldots, x_n]$ is the variables vector; $\overrightarrow{P} = [p_1, p_2, \ldots, p_n]$, P is random point on the hyperplane; and $d = \overrightarrow{H}.\overrightarrow{P} = \sum_{j=1}^{n} h_jp_j$. Regarding the position $\overrightarrow{X_i}$ as any point on the hyperplane, and taking $\overrightarrow{A_i}$ as the normal of the hyperplane, then we can obtain the hyperplane of $\overrightarrow{C_i^t}$ (the cruising vector of i-th golden eagle in iteration t) is given as:

$$\sum_{j=1}^{n} a_j x_j = \sum_{j=1}^{n} a_j^t x_j^* \tag{3}$$

In the formula, A_i is set to $\{a_1, a_2, \ldots, a_n\}$ that is the attack vector; X_i is set to $\{x_1, x_2, \ldots, x_n\}$ is the decision/design variables vector, $X^* = \{x_1^*, x_2^*, \ldots, x_n^*\}$ is the location of the selected prey. After calculating the cruise hyperplane of the eagle in the iteration, the cruise vector of the *i-th* golden eagle can be found in this hyperplane as follows.

$$c_k = \frac{d - \sum\limits_{j, j \# k} a_j}{a_k} \tag{4}$$

where c_k is the *k-th* element of the destination point C. a_j is the $j-th$ element of the attack vector A_i. d is the right-hand side of the Eq.(2). a_k^t is the $k-th$ element of the attack vector A_i, and k is the index of the fixed variable. Random target points on the cruising hyperplane is then the general representation of the target point on the cruise hyperplane.

$$\overrightarrow{C_i} = \{c_1 = random, c_2 = random, ..., c_k = \frac{d - \sum\limits_{j, j \# k} a_j}{a_k} ..., c_n = random\} \tag{5}$$

The eagle's displacement is measured by attack vector. The step size vector of the golden eagle is defined in iteration as follows.

$$\Delta x_i = \overrightarrow{r_1} p_a \frac{\overrightarrow{A_i}}{\left\|\overrightarrow{A_i}\right\|} + \overrightarrow{r_2} p_c \frac{\overrightarrow{C_i}}{\left\|\overrightarrow{C_i}\right\|} \tag{6}$$

where p_a^t is the attack coefficient in iteration t. p_c^t is the cruise coefficient in iteration t. $\overrightarrow{r_1}$ and $\overrightarrow{r_2}$ are random vectors whose elements lie in the interval [0,1]. The calculation of the Euclidean norm of $\|\overrightarrow{A_i}\|$ and $\|\overrightarrow{C_i}\|$ can be expressed as follows.

$$\left\|\overrightarrow{A_i}\right\| = \sqrt{\sum_{j=1}^{n} a_j^2}, \left\|\overrightarrow{C_i}\right\| = \sqrt{\sum_{j=1}^{n} c_j^2} \tag{7}$$

The golden eagle position update formula is shown following expression.

$$x^{t+1} = x^t + \Delta x_i^t \tag{8}$$

If the fitness of the golden eagle's new position is better than its remembered position, the eagle's memory is updated to the new place. Otherwise, the memory location remains the same, but the eagle will reside in the new location. In the latest iteration, each golden eagle randomly selects a golden eagle from the population to hover around the position with the best memory, calculates the attack vector, calculates the cruise vector, and finally calculates the step vector and the new position of the next iteration. The loop is executed until any termination conditions reach. Tow parameters p_a and p_c are used to shift from exploration to exploitation in GEO [17]. In the initial stage, p_a is low and p_c is high that is expressed as iteration progresses, p_a gradually increases and p_c gradually decreases.

$$\begin{cases} p_a = p_a^0 + \frac{t}{T}\left|p_a^T - p_a^0\right| \\ p_c = p_c^0 + \frac{t}{T}\left|p_c^T - p_c^0\right|, \end{cases} \tag{9}$$

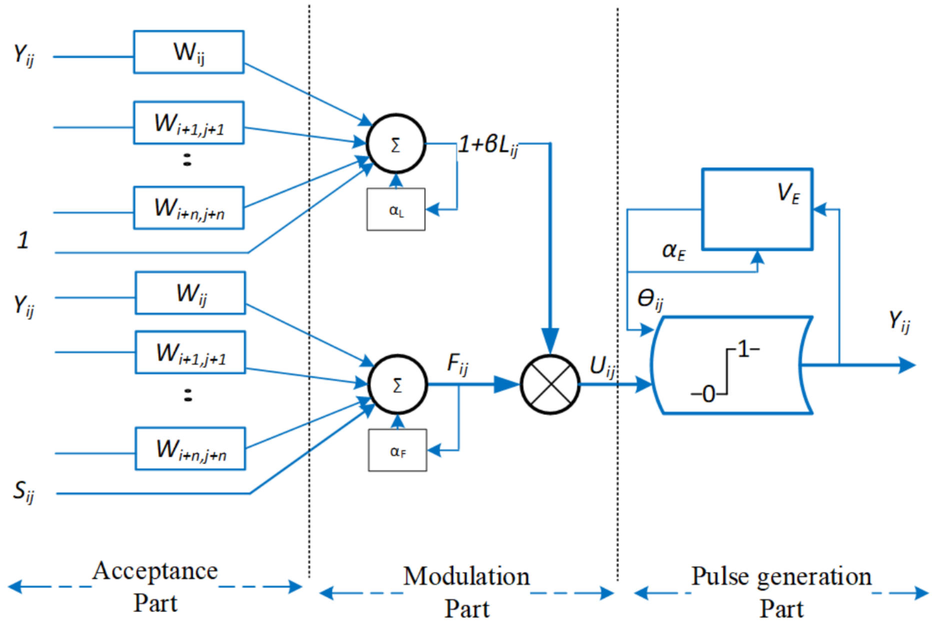

FIGURE 1. An example of a pulse coupled neural network (PCNN) structure

where t represents the current number of iterations, and T represents the maximum number of iterations. p_a^0 and p_a^T are the initial and final values of the attack propensity respectively. p_c^0 and p_c^T are the initial and final values of cruise tendency respectively. $[p_a^0, p_a^T]$ is set to $[0.5, 2]$ and $[p_c^0, p_c^T]$ is set to $[1, 0.5]$ that means that p_a; p_c linearly increases from 0.5 and 0.5 to the end of the iteration.

3. **An Optimizing PCNN Parameters based on GEO.** Combined with the GEO algorithm and PCNN model characteristics, each golden eagle represents a candidate solution to the optimal parameters problem. Each golden eagle's position is a vector composed of the output of PCNN parameters in setting the medical image segment.

$$X = \begin{bmatrix} x_1^1 & \dots & x_i^1 & \dots & x_1^1 \\ \dots & \dots & \dots & \dots & \dots \\ x_1^i & \dots & x_i^i & \dots & x_n^i \\ \dots & \dots & \dots & \dots & \dots \\ x_1^n & \dots & x_1^n & \dots & x_n^n \end{bmatrix} \tag{10}$$

where X is the output golden eagle matrix of the generator set, and the row vectors of matrix X represent the specific positions of each eagle. The PCNN optimal parameter outcome is figured out as the golden Eagle optimization algorithm needs to randomly generate the golden eagle position in the preliminary trial stage.

$$X = L_{bound} + R_{rand}(U_{bound} - L_{bound}) \tag{11}$$

where R_{rand} is a random number evenly distributed between 0 and 1. L_{bound} is the output lower limit matrix of the generator set and U_{bound} is the output upper limit matrix of the generator set. The fitness function, which is a crucial aspect of the optimization method, impacts segmentation results. The quantity of information in the target can be represented by entropy, and the higher the entropy, the more data it holds [6]. As a result, the fitness function is expressed as the segmented image's entropy.

$$H = -p_1 \times \log_2 p_1 - p_0 \times \log_2 p_0, (0 < p_0, p_1 \leq 1) \tag{12}$$

where p_1 is the ratio of 1 in the binary image to the whole image; p_0 is the proportion of 0 in the binary image to the whole image. A structure of the PCNN model is considered as the three sections: inputs as acceptance, modulation and pulse generator places. Figure 1 shows a pulse coupled neural network structure. The mathematical model of the PCNN expression is given as follows.

$$F_{ij}[n] = S_{ij} \tag{13}$$

$$F_{ij}[n] = \sum W_{ijkl} Y_{kl}[n-1] \tag{14}$$

$$U_{ij}[n] = F_{ij}(1 + \beta L_{ij}[n]) \tag{15}$$

$$\theta_{ij} = \exp(-\alpha_E)\theta_{ij}[n-1] + V_E Y_{ij}[n-1] \tag{16}$$

$$Y_{ij}[n] = \begin{cases} 1, U_{ij}[n] \geq \theta_{ij}[n] \\ 0, U_{ij}[n] < \theta_{ij}[n] \end{cases} \tag{17}$$

where $F_{ij}[n]$ and $S_{ij}[n]$ are the inputs and the external inputs of a PCNN, respectively, such as all pixels of an image; $L_{ij}[n]$ and $U_{ij}[n]$ are is the connected input links and the internal active term; $\theta_{ij}[n]$ and $Y_{ij}[n]$ are the dynamic threshold and the output of neural network respectively; β and W_{ij} are the connection coefficient and connection matrix; α and V_E is the is the threshold attenuation coefficient and threshold amplification coefficient. The matrix weight W_{ij} can be set as follows.

$$W_{ij} = \begin{bmatrix} 0.706 & 1 & 0.706 \\ 1 & 0 & 1 \\ 0.706 & 1 & 0.706 \end{bmatrix} \tag{18}$$

Among these parameters, there are three main factors: β, α_E, and V_E: connection coefficient, threshold attenuation coefficient, and threshold amplification coefficient, which have a great influence on segmentation results [6].

Therefore, the three effective parameters of the PCNN are connection coefficient β, threshold attenuation coefficient α_E and threshold amplification coefficient V_E will be optimized by applying the GEO. The medical image segmentation is realized automatically through analysis by the obtained optimal value into the PCNN. Figure 2 shows the basic flow chart of the GEO with PCNN parameters for the image segmentation.

The algorithm implementation process is implemented process as follows.

Step 1: Initialize golden Eagle basic parameters and images; All golden eagles are randomly initialized between the upper and lower bounds of the output PCNN parameters, and the fitness function value is used by Eq (20).

Step 2: Take the medical image as the input data scheme; the GEO obtains the fitness function values of the PCNN parameters over iteration by optimizing the solution containing the three PCNN parameters, compares the obtained fitness function with the prevoius, and retains the optimal local parameters. Update the position, attack factor, cruise factor, and fitness value of the golden eagle. If it is in the first generation, the current position of the initial population of the golden eagle is directly used as the optimal position of the golden eagle memory. In the iterative process, the golden eagle randomly selects a prey from the population's memory and calculates the current target's corresponding attack coefficient and cruise coefficient.

Step 3: Golden Eagle updates the current position and calculates the fitness value for the new place. Judge whether the fitness value is better than the fitness value in the memory of the golden eagle; if it is better than the fitness value in the memory of

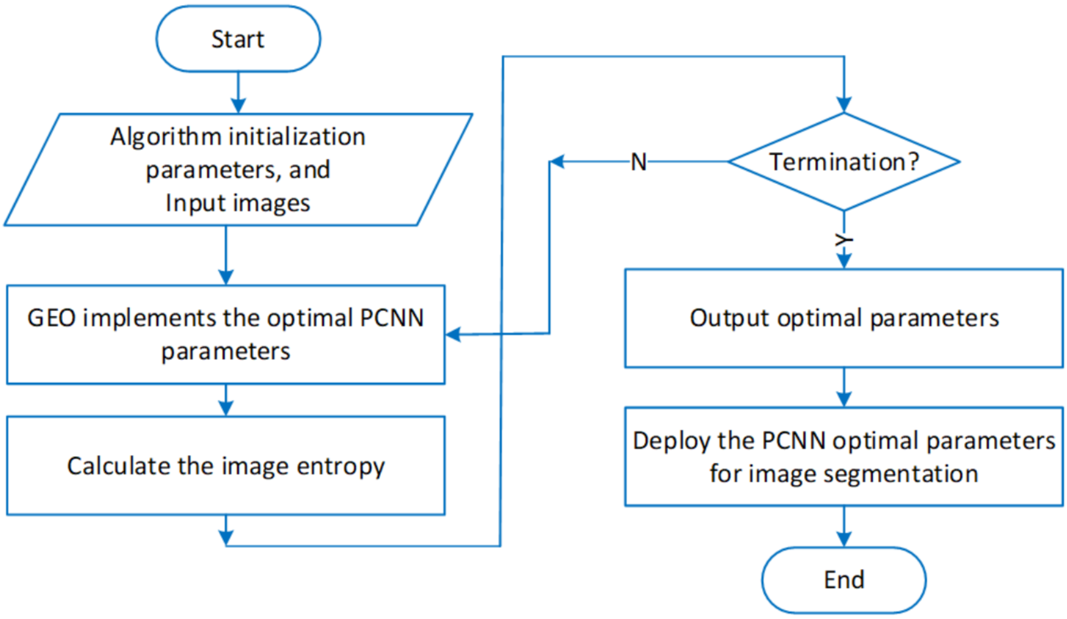

FIGURE 2. A flow chart of the GEO with PCNN parameters for the image segmentation

the golden eagle, update the optimal position in the memory of the golden eagle, and otherwise do not change.

Step 4: Termination condition: The iteration is terminated if the maximum number of iterations is reached. Output the optimal dispatching scheme (the best golden eagle memory) and power generation cost (the best fitness value of golden eagle) for the PLD problem; otherwise, go to Step 2 and repeat the iterative process until the end meets the termination condition.

Step 5: The optimal parameters are brought into PCNN to realize image segmentation.

4. **Experimental Results and Discussion.** Some images are selected from the brain image database [19] are used to test the proposed scheme's performance. Figure 3 depicts the selected medical images with different slices. The optimal results of the suggested method of the GEO are compared with the other techniques in the literature, e.g., GA [13], PSO [12], SCA [14], and GWO [15] algorithms for the PCNN optimal parameters. The environment setting for the algorithms are the same condition, e.g., MaxIteris set to 300; the runs number is set to 30; the population size is set to 60; and the average value of each evaluation standard.

The ideal segmentation effect can be obtained using the image entropy as the fitness function according to Eq. (12), where P0 and P1 are set to 1/2, the maximum entropy of the segmented image can be obtained. In exceptional cases, when the proportion of the background and the target of the original image in the whole picture is significantly different, it causes a reduced segmentation effect. The target and background of the binary image should also account for about 50% of the image so that the medical image can achieve a good segmentation effect. Figure 4 shows the comparison of the curve of the proposed scheme with the GA [13], PSO [12], SCA [14], and GWO [15] algorithms combined with PCNN in the various slices of the images. Observed that the curve of the suggested GEO produces a better convergence curve than the other schemes in competitors.

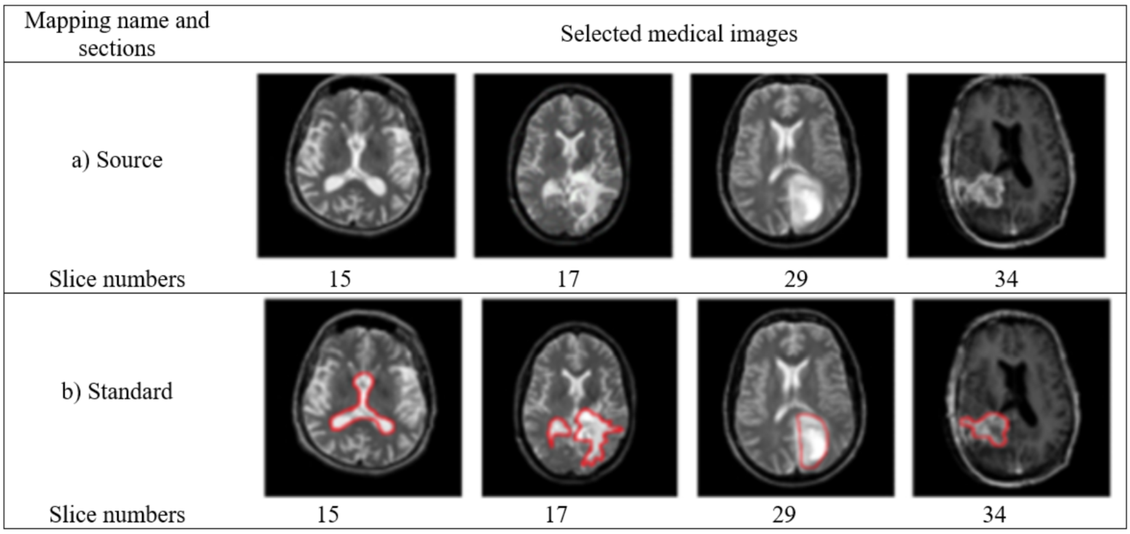

FIGURE 3. The selected medical images with different slices

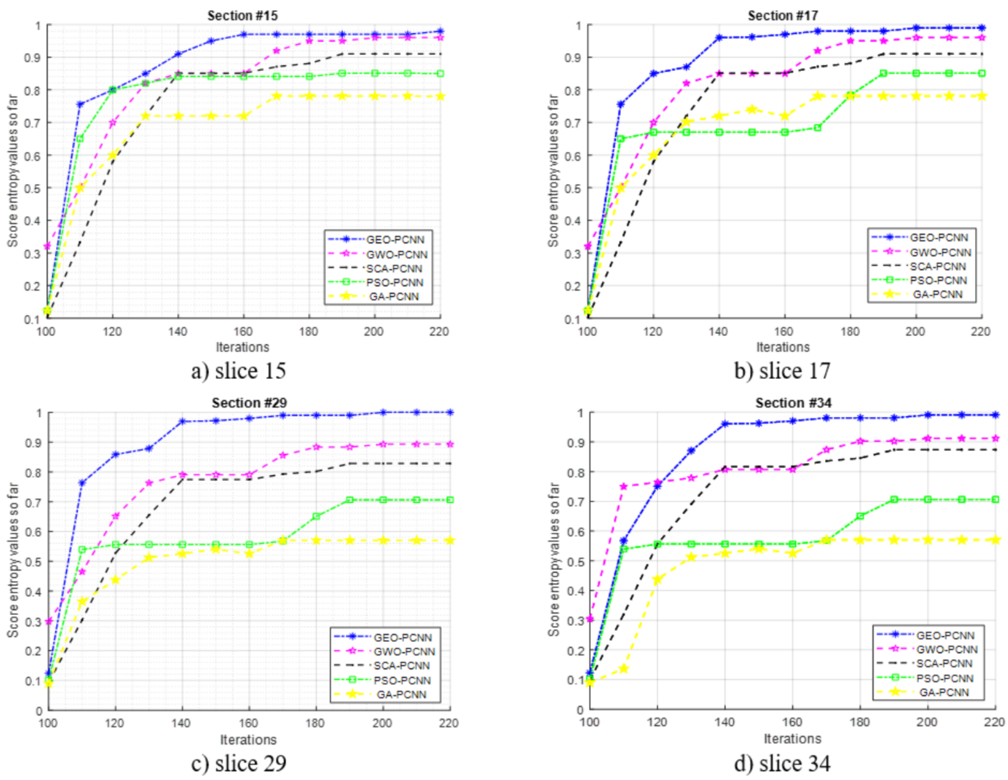

FIGURE 4. The comparison of the curve of the proposed scheme with GA, PSO, SCA, and GWO algorithms combined with PCNN in the various slices of the images.

Three evaluation criteria are used to quantify the segmentation results as the factor of the precision, recall, and dice [19-21] are expressed as follows.

$$accuracy = \frac{TP}{TP + FP} \tag{19}$$

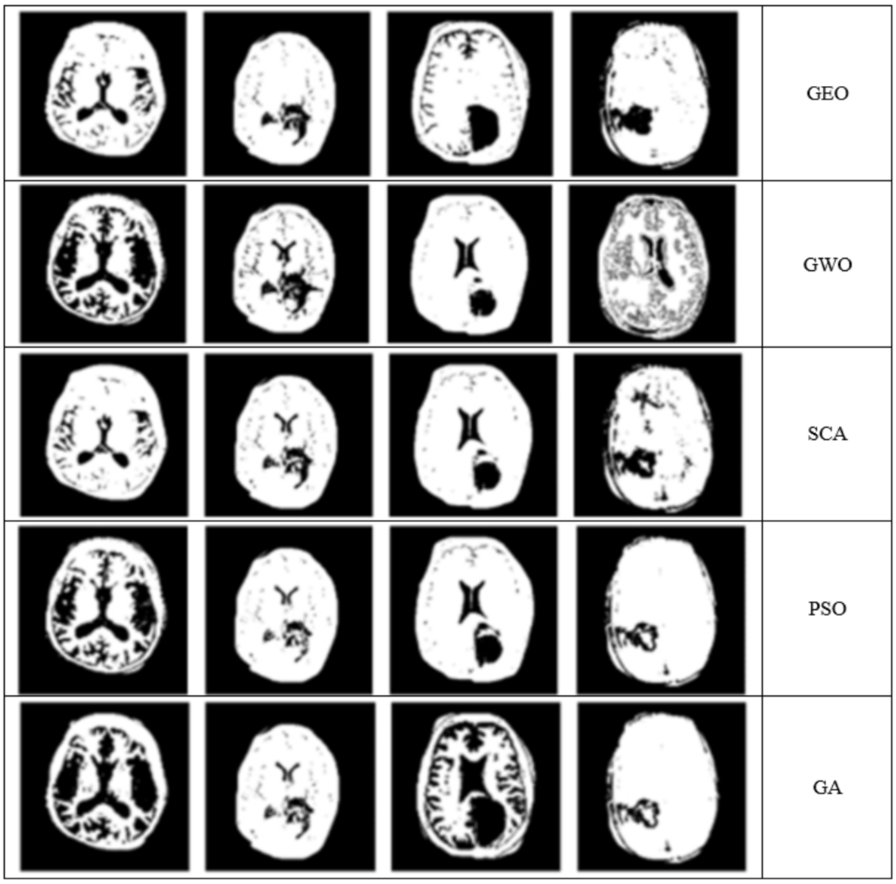

FIGURE 5. The medical segmentation effect through the different schemes

$$recall = \frac{TP}{TP + FN} \tag{20}$$

$$dice = \frac{2TP}{(TP + FP) + (TP + FN)} \tag{21}$$

where TP is the part where the target region coincides with the segmentation result, FP is the non target region in the segmentation result, and FN is the part not included in the segmentation result. The closer the value of these three evaluation criteria to 1, the better the segmentation effect. Figure 5 shows the medical segmentation effect through the different schemes. From the Figs 3b and 5, we can clearly see that the proposed method has higher segmentation accuracy, clearer segmentation contour, and is closer to the vision.

Figure 6 shows the comparison of evaluation criteria of each algorithm combined with PCNN in comparison with other methods, e.g., GA, PSO, and GWO schemes for the automatic medical image segmentation. The figure shows that each image's GEO evaluation standard value is higher than other algorithms, which shows that the proposed algorithm has high segmentation accuracy and robustness. The final results of the GEO algorithm in terms of evaluation criteria of accuracy, recall, and dice rates are 0.977, 0.772, and 0.846, respectively. Therefore, the GEO-PCNN has some advantages over other algorithms in search efficiency and precision.

5. **Conclusions.** This paper suggested a new solution to optimizing pulse-coupled neural network (PCNN) parameters with the golden Eagle optimization algorithm (GEO) for

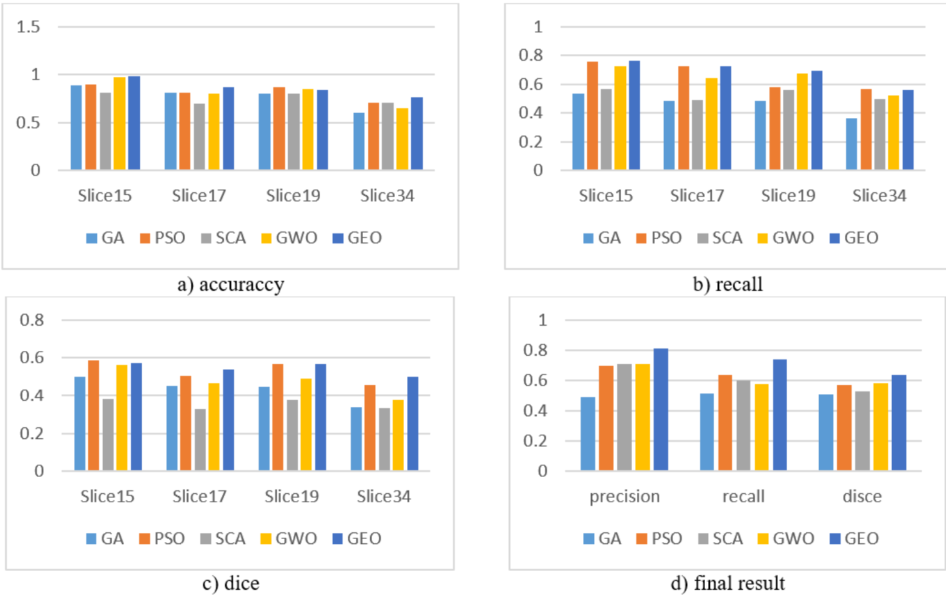

FIGURE 6. Comparison of evaluation criteria of each algorithm combined with the PCNN

automatic image segmentation. Traditional methods for the optimal PCNN parameters would encounter computational complexity time as exponential complexity. The swarm intelligence optimization algorithm is one of the most effective approaches of dealing with the computational exponential complexity time issues. GEO is a new robust swarm intelligence optimization algorithm that owns advantages that is the first time applied to deal with the PCNN features that would assist in reducing the difficulty of establishing segmentation impact remains unchanged. The fitness function is figured out as image entropy, and selected brain MRI images are used to verify the proposed scheme for the experiment. The obtained result of the GEO method integrated with PCNN compared to the other optimization techniques shows that the proposed method has a higher segmentation accuracy and resilience and a higher technical application value. In the future, the fitness function of the algorithm will be further explored to find a more rapid [22-23] and effective methods [24-25].

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