ITC 2/52
Information Technology and Control
Vol. 52 / No. 2 / 2023
pp. 487-499
DOI 10.5755/j01.itc.52.2.33415

Image Segmentation Combining Pulse Coupled Neural Network and Adaptive Glowworm Algorithm

Received 2023/02/14 | Accepted after revision 2023/03/28

HOW TO CITE: Zhu, J., Ma, Y., Huang, J., Wang, L. (2023). Image Segmentation Combining Pulse Coupled Neural Network and Adaptive Glowworm Algorithm. *Information Technology and Control*, 52(2), 487-499. https://doi.org/10.5755/j01.itc.52.2.33415

Image Segmentation Combining Pulse Coupled Neural Network and Adaptive Glowworm Algorithm

Juan Zhu

School of Mechatronic Engineering, Changchun University of Technology, Changchun 130022, China

Yuqing Ma, Jipeng Huang

School of Physics, Northeast Normal University, Changchun 130024, China

Lianming Wang

School of Marine Science and Technology, Hainan Tropical Ocean University, Hainan, 572022, China

Corresponding author: huangjp848@nenu.edu.cn

Image segmentation is one of the key steps of target recognition. However, the accuracy of image segmentation is still challenging. To solve this problem, an image segmentation algorithm combining Pulse Coupled Neural Network(PCNN) and adaptive glowworm algorithm is proposed. The algorithm retains the advantages of the glowworm algorithm. Introduce the adaptive moving step size and the population optimal value as adjustment factors. Enhance the ability to solve the global optimal value of the fitness function. Take the weighted sum of the cross entropy, information entropy and compactness of the image as the fitness function of the glowworm algorithm. This function can ensure the visual effect of image segmentation and limit the running time while maintaining as much as possible the original information of the image. In order to intuitively evaluate the effect of the segmented image, use a number of segmentation evaluation parameters to quantify the image. Maintain the diversity of image features and improving the accuracy of image segmentation. Experimental results show that compared with other algorithms, the segmented image obtained by this algorithm has better visual effect and the segmentation performance has the best comprehensive performance. For the seven gray-scale images in the Berkeley segmentation dataset, the segmentation effect is improved by 10.85% compared with two-dimensional entropies(TDE), 9.22% compared with Genetic Algorithm(GA), and 22.58% compared with AUTO algorithm.

KEYWORDS. Image Segmentation; Glowworm Swarm Optimization Algorithm; Pulse Coupled Neural Network; Fitness Function.

1. Introduction

Image segmentation is important in image processing. Image segmentation is the operation of grouping and clustering pixels according to the gray level, texture and other characteristics. Divide the image into several consistent non overlapping regions [17]. The quality of segmentation results will directly affect the subsequent feature extraction and target recognition. Thus, image segmentation is one of the key of recognition effect.

Various segmentation methods have been proposed after extensive research by scholars at home and abroad. At present, image segmentation methods mainly include threshold segmentation method [1, 26, 10], edge detection method [35, 24, 8] and neural network method [23, 15, 20, 4]. The principle of threshold segmentation method is to find an appropriate threshold and divide the image into target or background according to the gray value of image pixels. Its advantage is simple calculation and short time, but the quality of segmentation results depends on the selection of threshold. Edge detection is to find the local discontinuous edge points of the image through derivation operation, and connect them into a closed curve according to a certain strategy, so as to separate the target from the background. Its advantage is sensitive to the edge gray jump. However, if the gray value of the target boundary is close to that of the adjacent background, false segmentation will occur. Artificial neural network (ANN) simulates the neural system to process complex information. It is a biological mathematical model. Its advantage is to carry out machine learning through the establishment of database. It has strong universality and broad application prospects. However, in the process of establishing neural network, a large number of test samples are often required. The image segmentation effect is poor for a small database.

With the evolution and maturity of neural network, PCNN has been favoured by scholars in image segmentation [9, 6, 7]. As the third generation of neural network, PCNN does not need to train samples. By changing the setting of initial parameters, PCNN can better deal with the overlap between image target and background area, and supplement the image space gap caused by small gray difference, so as to make the segmented image more complete. However, PCNN also has some disadvantages. Its original model is complex, there are so many parameters that it is difficult to debug automatically. There are some limitations in practical application. Therefore, scholars often simplify and adjust PCNN in combination with specific applications.

Zhang et al. [31] fused PCNN and AD into a parallel system, optimized the parameters of PCNN by using adaptive Pareto GA and applied it to image denoising. It applied the elite selection system and the last elimination system combined with greedy algorithm. Transplant the idea of swarm intelligence algorithm into image segmentation, which had also achieved good results. However, in some pictures, whose gray value background is close to the target were also classified into the target area, which had some defects. Lian et al. [14] automatically determined the link coefficient by using the spatial and gray characteristics of the segmented image. Add a control parameter to the model to judge whether the image was over segmented or under segmented. This method had low computational complexity, but it was too sensitive to image details or noise, which will be segmented together and affect the overall effect of the image. Zhao et al. [34] used adaptive pulse coupled neural network (PCNN) in firefly optimization in remote sensing image fusion. It got good experimental result in remote sensing image.

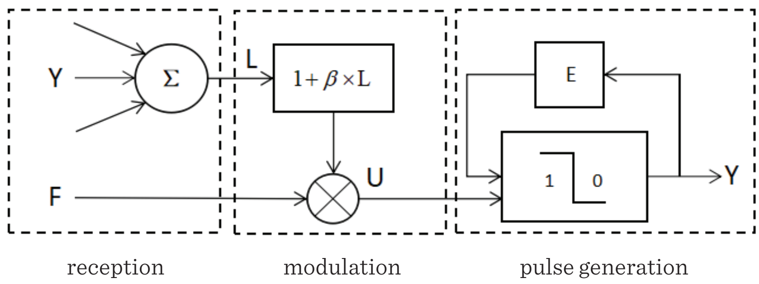
To solve the problems existing in the above algorithms, combine the advantages of the above algorithms, an image segmentation method based on PCNN and Glowworm Algorithm is proposed in this paper. The experimental results show that compared with the above methods, the proposed method has the best comprehensive effect on image segmentation, and can better realize the accurate processing of complex images.

2. PCNN Model

In 1990, inspired by the phenomenon of pulse synchronous release in cat cerebral cortex, Eckhorn proposed PCNN [3]. Then, Rangnanath et al. constructed PCNN model based on it, in which the signal morphology and processing mechanism were more in line

Figure 1

A simplified model of PCNN



with the physiological basis of human visual nervous system [18].

PCNN belongs to a single-layer neuron model. In the practical application of image processing, in order to make it work better and simplify the operation, many scholars have made different modifications to the PCNN model [2, 5, 29, 21, 30]. This paper adopts the simplified model proposed by Gu [27]. The simplified PCNN model is shown in Figure 1, which mainly includes three parts: reception, modulation and pulse generation.

The iterative equation is as follows:

$$F_{ij}[n] = S_{ij} \tag{1}$$

$$L_{ij}[n] = \sum_{kl} W_{ijkl} Y_{kl}[n-1] \tag{2}$$

$$U_{ij}[n] = F_{ij}[n](1+\beta L_{ij}[n]) \tag{3}$$

$$E_{ij}[n] = e^{-\alpha_e} E_{ij}[n-1] + v_e Y_{ij}[n-1] \tag{4}$$

$$Y_{ij}[n] = \begin{cases} 1, U_{ij}[n] > E_{ij}[n] \\ 0, otherwise \end{cases} \tag{5}$$

PCNN model obtains the final result of image segmentation by iterating the above equations. Where, n is the number of iterations, which affects the overall segmentation effect of the image. F_{ij} and L_{ij} are feedback input and connection input respectively, and W_{ijkl} is the weighting coefficient matrix of Y_{kl}, which defines the communication intensity between neighbourhood neurons and central neurons. β is the connection strength constant between neurons, which adjust the intensity of management neighbourhood neurons affecting the ignition cycle of central neurons. U_{ij} is an internal activity item that integrates the modulated F_{ij} and L_{ij}. E_{ij} is the dynamic threshold of neurons and AE is the attenuation constant of E_{ij}, which controls the rate of threshold decline. v_e is the inherent potential of Y_{ij}, which is used to adjust the ignition cycle of neurons, and Y_{ij} is the output pulse.

At the beginning of the iteration, the neurons will map to the pixel points of the image and correspond to them one by one. The normalized pixel values are converted into the input of the F_{ij} channel of the corresponding neurons. The output of adjacent neurons is converted into the input of the L_{ij} channel by weighting operation. In the process of image segmentation, each neuron has only two output states: ignition or extinction. First, a global zero threshold is given so that all pixels are activated in the first iteration, and its dynamic threshold E_{ij} increases instantaneously. Then, with the increase of the number of iterations, the threshold begins to decay exponentially. When it decays below the internal active item U_{ij}, the pixels are activated again.

In image segmentation, suppose the target of the image is bright and the background is dark. The brightness of the target is greater than the background, the neurons corresponding to the target are ignited first. The neurons corresponding to the background are extinguished. By transmitting the pulse sent by the bright area to the neighborhood, the synchronous ignition of the neurons in the dark area adjacent to the bright area can be triggered, and the regional segmentation of the image is realized.

There are many parameters to be determined in PCNN network model. In PCNN simplified model, β, α_e, v_e and n need to be set. PCNN model mainly has two parameter setting schemes, user-defined value and adaptive value. Among them, the user-defined value needs to take random values for the corresponding pictures for multiple segmentation experiments. Modify the parameters according to the final results. It has a great degree of subjectivity. It is difficult to obtain the ideal image segmentation effect for the pictures outside the experiment. The adaptive value is to automatically optimize and find the parameters according to the parameter formula or swarm intelligence algorithm. Compared with the equations, the segmented image effect obtained by applying swarm intelligence algorithm for parameter optimization is greatly improved, which is more widely used and has strong universality.

3. Swarm Intelligence Algorithm

Swarm intelligence algorithm is a bionic algorithm that simulates the swarm intelligent behavior of insects and swarm animals in nature. The key to the successful application of swarm intelligence algorithm lies in the self-organization within the group and the principle of reasonable task division [19], because it can effectively deal with nonlinear optimization problems. At the same time, it has the characteristics of fast convergence, which has attracted the attention of many scholars and has been widely used.

3.1. The Method of Glowworm Swarm Optimization

β, α_e, v_e and n are the core of configuring PCNN network. In order to find the best configuration scheme of parameters and improve the effect of image segmentation, this study uses adaptive glowworm algorithm to optimize PCNN neural network. Glowworm swarm optimization was proposed by Krishnanand and Ghose in 2005, which is called GSO for short [11]. Similar with glowworm algorthim [28], GSO has the advantages of simple model, strong global search and optimization ability and easy implementation.

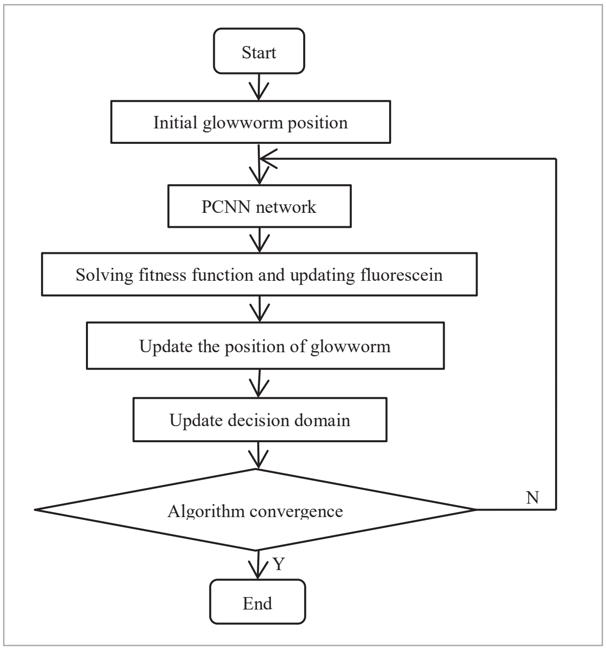
Suppose each glowworm is $X(\alpha_e, v_e, n, \beta)$ corresponding to a parameter configuration scheme. The process of searching the best glowworm is the process of finding the optimal configuration scheme of PCNN parameters. The quality of glowworm is determined by the fitness function of GSO parameter optimization model. The fitness function corresponds to the objective function of optimization problem. In the model, n glowworms in the population are randomly distributed in the solution space at first. The initial brightness of glowworms is calculated according to the current position, and then the fitness function value of glowworms is solved according to the diffusion rate of fluorescein. Then, the position of glowworms in the whole population is optimized again according to the attraction rules between glowworms, and the individual decision domain is updated. Thus, the current fitness function value of the individual can be continuously improved. After a certain number of position optimization, the whole population can be collected to the optimal coordinates to obtain the optimal solution.

The flow chart of GSO is shown in Figure 2.

GSO is divided into four parts [16]:

1 Initialize the location and decision domain of the glowworm;

Figure 2
Flow chart of GSO



In the initial state, each glowworm has the same decision domain. The capacity of the decision domain determines how many neighboring glowworms attract the current glowworm.

2 Update fluorescein to obtain the current fitness function of glowworm;

The intensity of individual glowworm fluorescein is affected by its objective function value. After an individual moves, the intensity of fluorescein will change with the objective function value of its current position. The basis for updating fluorescein is as follows:

$$l_i(n+1) = (1-\rho)\times l_i(n) + \gamma J_i(n+1). \tag{6}$$

In Equation (6), ρ is the delay factor of fluorescein. γ is the renewal rate of fluorescein. J_i is fitness function value.

3 Update the position of glowworm;

The individual glowworm will be attracted by the glowworm whose brightness is higher than it in the decision domain and move towards it. The probability of glowworm i moving towards its adjacent glowworm j is as follows:

$$p_j(n) = \frac{(l_j(n)-l_i(n))}{\sum_{k\in N_i(T)}(l_k(n)-l_i(n))} \tag{7}$$

$N_i(T)$ is number of glowworms in decision domain.

The position changes of glowworms are as follows:

$$x_i(n+1) = x_i(n) + s\times\left(\frac{x_j(n)-x_i(n)}{\left\|x_j(n)-x_i(n)\right\|}\right), \tag{8}$$

where S is the step.

4 Update the glowworm's decision domain.

In order to prevent the algorithm from stalling due to the constant number of glowworms in the decision domain, the decision domain of glowworms should be updated in each round of movement. In the GSO algorithm, the radius of the glowworm individual decision domain is adjusted according to the change of the number of glowworms in the neighborhood. The update rule is shown in the formula:

$$r_d^i(n+1) = \min\left\{r_s, \max\left\{0, r_d^i(n) + \beta\left(n_t - \left|N_i(n)\right|\right)\right\}\right\} \tag{9}$$

Here β is 0.08. n_t is the threshold for sensing the number of glowworm in a neighborhood.

3.2. Improved Glowworm Optimization Algorithm

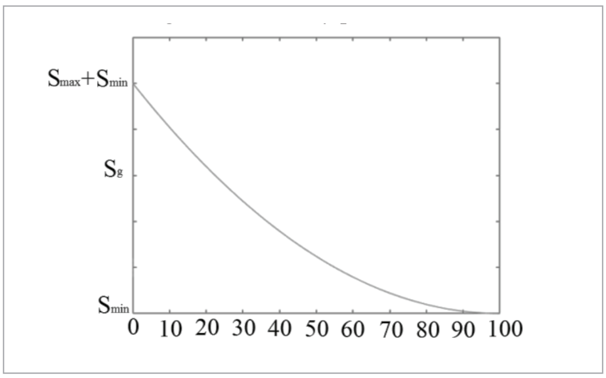
According to the definition of GSO algorithm, in the early stage of the algorithm, in order to make individual glowworms converge near the best point as soon as possible, a larger step size is required. In the later stage of the algorithm, due to the basic convergence of the algorithm, a larger step size will cause glowworms to oscillate near the best point. It can be seen that the fixed step size is the main reason for the slow convergence speed and low accuracy of GSO algorithm. Therefore, the use of fixed step size in the whole process can not meet the requirements of step size in the initial stage and later stage of the algorithm at the same time. In this paper, the convergence and solving ability of the algorithm are improved by introducing dynamic step size.

$$s = \left(\left(s_{\max} - s_{\min}\right)\times\frac{T-t}{T}\right)^{e^{-0.7}} + s_{\min}, \tag{10}$$

where $s_{\max}$ is the maximum step size, $s_{\min}$ is the minimum step size, T is the total number of iterations, and t is the current number of iterations.

The modified step function curve is shown in Figure 3. The minimum step size can ensure that the individual glowworm has enough strong moving ability in

Figure 3
The modified step function curve



the initial stage, which is used to improve the running speed of the algorithm in the formula. The maximum step size is used to ensure the distance of glowworm each move in a certain range. It can prevent the algorithm accuracy problems.

Meanwhile, in the process of glowworm movement, GSO algorithm ignores the guiding role of the optimal value of individuals in the population. Only considering the local information in the neighborhood set will make the communication between glowworm populations not timely, converge slowly and fall into the local optimal solution, which is not conducive to the evolution of the population. According to the brightness performance of individual glowworms, they are divided into two categories. The movement mode of ordinary glowworms is as follows:

$$x(t+1) = x(t) + s \times (x(g_{bestflv}) - x(t)) \tag{11}$$

The optimal value of the population or the movement mode of no other brighter glowworms in the neighborhood is

$$x(t+1) = x(t) + \alpha \times (rand - 0.5)\,. \tag{12}$$

The introduction of swarm intelligence algorithm into PCNN neural network, which combines random movement and approaching the population optimal solution, can effectively avoid the algorithm falling into the local optimal solution and greatly shorten the overall convergence time of the algorithm. At the same time, if the population size is too large, the times of fitness evaluation will increase and the calculation time will increase; If the population size is too small, it may cause immature convergence, and the reliability of the solution is not high. Here, the population size is taken as 30 and the maximum number of iterations is set as 30.

Compared with the traditional glowworm algorithm, the improved glowworm algorithm not only improves the global optimization ability and reconciliation accuracy of particles, but also greatly shortens the running time and greatly improves the performance.

The flow chart of improved glowworm algorithm is as follows.

Step 1: The population was initialized. Set the parameters of fluorescein volatilization factor, fluorescein renewal rate, and the capacity threshold of glowworm. Add two parameters s_{max} and s_{min}.

Step 2: The current fitness value was calculated according to the individual position and fitness function, and then the individual fluorescein concentration was updated.

Step 3: The glowworms were divided into two groups according to the current fluorescein concentration of the population. The position of glowworms was updated according to the category of glowworms.

Step 4: Step 2 is returned when the number of iterations is not full or the convergence condition is not reached, and the algorithm terminates when the algorithm converges.

4. Improved Glowworm Algorithm to Optimize PCNN

When applying swarm intelligence optimization algorithm to image segmentation, we must first clarify how to correctly associate image segmentation with swarm intelligence optimization algorithm.

4.1. Fitness Function

In the intelligent algorithm of glowworm swarm, the position of glowworm determines the current fitness value of glowworm, so the coordinates of glowworm individual can be used as the independent variable in the fitness function. Whether the fitness function is appropriate will determine whether the image segmentation effect is good. In this way, the introduced swarm intelligence algorithm transforms the image segmentation problem into the optimization problem of the fitness function, that is, the ideal image segmentation result can be obtained by setting the optimal fitness function [32].

Due to the complexity of the test image itself, different images have different features. Using a single feature coefficient as the fitness function will make the segmentation error larger. When adding multiple feature coefficients directly, the effect of a single feature coefficient will be ignored. Therefore, how to give the weight of each feature coefficient has become a key problem.

In order to make the given fitness function improve the image segmentation effect as much as possible, maintain the diversity of image features, and eliminate the over segmentation or under segmentation caused by a single feature, this experiment selects multiple groups of fitness functions from multiple image samples for testing, and selects the weighting coefficient according to the effect of image segmentation. After many experiments, this paper finally selects the weighted sum of image information entropy, cross entropy and compactness as the fitness function of glowworm swarm intelligent search.

Information entropy represents the overall characteristics of the information source in an average sense and represents the overall uncertainty of the information source. The greater the value is, the greater the uncertainty of the information source. The greater the amount of information is, the better the segmentation effect. When it is applied to the fitness function, it can retain the important information in the image as much as possible [25]. The formula is defined as follows:

$$IE = -P_1 \times \log_2 P_1 - P_0 \times \log_2 P_0 \,, \tag{12}$$

where P1 and P0 are respectively the probability of the pixel value is 1and 0. IE is the overall entropy of the segmented image.

Cross entropy is proposed by Kullback [12] in the name of directed divergence, and is used to measure the information difference between the target and background probability distributions between the segmented image and the original image [13]. Taking the cross entropy function as one of the fitness functions can ensure the accuracy of image segmentation. The cross entropy parameter is defined as follows:

$$u_1(t) = \frac{1}{\sum_{f=0}^{t} h(f)} \sum_{f=0}^{t} f \times h(f) \tag{13}$$

$$u_2(t) = \frac{1}{\sum_{f=t+1}^{Z} h(f)} \sum_{f=t+1}^{Z} f \times h(f) \tag{14}$$

$$CE = \sum_{f=0}^{t} \left[f \times h(f) \times \ln \frac{f}{u_1(t)} + u_1(t) \times h(f) \times \ln \frac{u_1(t)}{f} \right] + \\ + \sum_{f=t+1}^{Z} \left[f \times h(f) \times \ln \frac{f}{u_2(t)} + u_2(t) \times h(f) \times \ln \frac{u_2(t)}{f} \right] \tag{15}$$

$$CEP = 1 - \frac{CE}{Z} \,, \tag{16}$$

where, f is the gray value of the image; $h(f)$ is the gray histogram of the image; Z is the maximum gray value of the image; $u_1(t)$ and $u_2(t)$ are the intra class mean values of background and target in the segmented image respectively; *CE* is cross entropy. The larger the CEP is, the more accurate the segmentation is.

While ensuring the maximum amount of information of the segmented image, we should also take into account the visual effect of the image. In order to prevent the image segmentation from being too broken, this paper introduces the compactness function into the fitness function. The compactness of image segmentation is the sum of the compactness of each pixel of the whole image. The higher the compactness of image segmentation, the better the segmentation effect [33]. After PCNN segmentation, the original image becomes a binary image, that is, the target is the part with gray value of 1 and the background is the part with gray value of 0. For a single pixel $c_{i,j}$, its compactness is determined by the neighborhood pixels together. When the neighborhood value is the same as the central value, the compactness is added by 1, otherwise it remains unchanged. After normalizing the total compactness, the compactness CPS can be obtained. Its calculation formula is as follows

$$CPS = \frac{1}{8} \times \frac{1}{m \times n} \times \\ \times \sum_{i=1}^{m} \sum_{i=1}^{n} \left(c_{i-1,j-1} + c_{i-1,j} + c_{i-1,j+1} + c_{i-1,j-1} + c_{i+1,j-1} + c_{i+1,j} + c_{i+1,j+1} \right). \tag{17}$$

The final fitness function is determined as follows:

$$objvalue = IE + 3 \times CEP + 0.5 \times CPS \,. \tag{18}$$

Its performance is better than the fitness function constructed by weighted summation of single fitness function or other characteristic functions. In the process of image segmentation, the overall and local information of the segmented image is fully retained, and each function is relatively independent, which reduces the interference caused by the redundancy of feature information in the process of weighted summation.

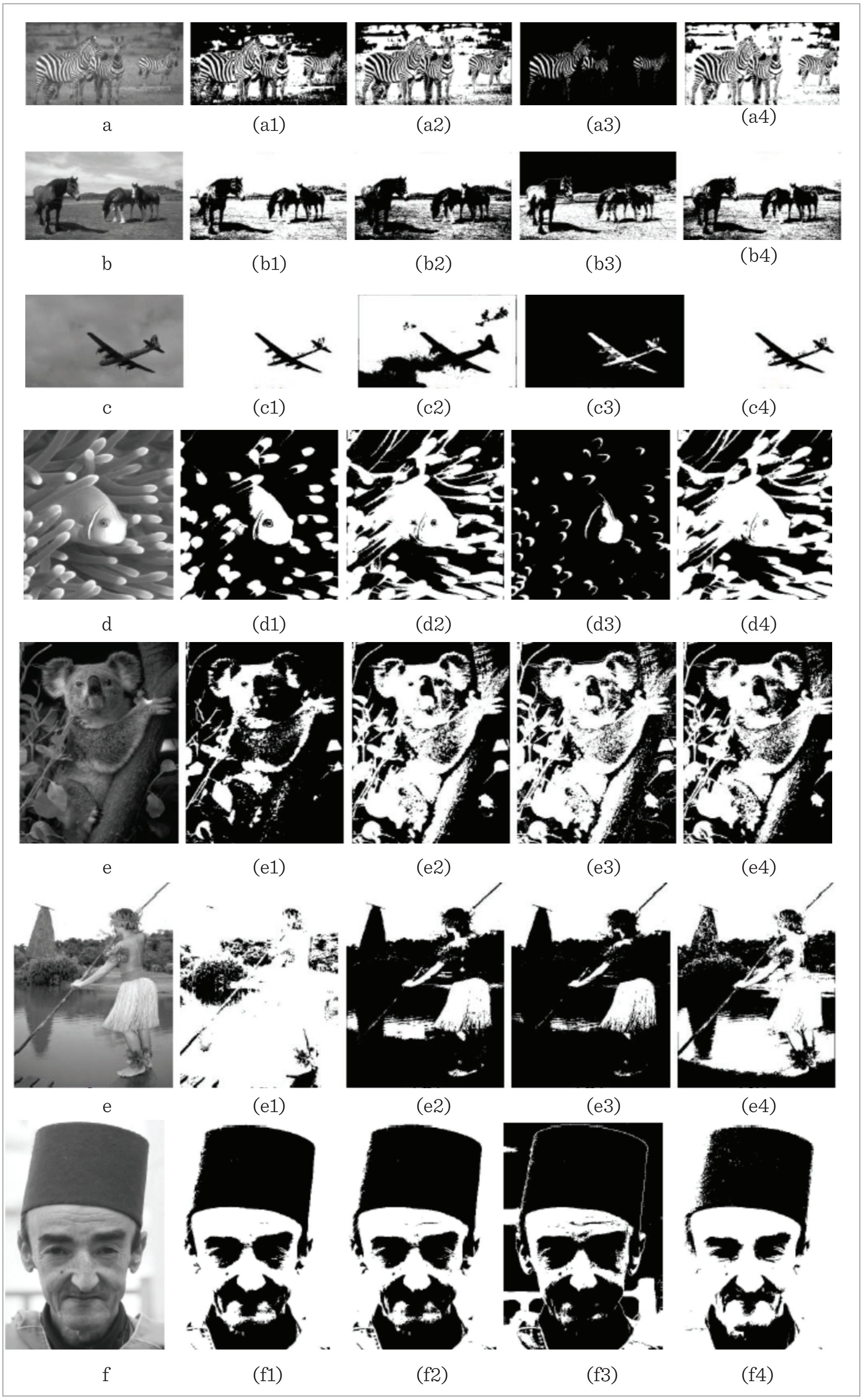


Figure 4
Image segmentation results (a–g is the original gray image, sub-graph 1 are the segmentation results of maximum two-dimensional entropy, sub-graph 2 are the segmentation results of GA-PCNN, sub-graph 3 are the segmentation results of the AUTO-PCNN method, sub-graph 4 are the segmentation results of the method proposed in this paper)

After substituting the fitness function into the improved glowworm algorithm, in order to verify the application effect of this algorithm in the actual situation, seven gray images in the Berkeley segmentation data set are segmented, and the segmentation results of this method are compared with the maximum two-dimensional entropy (TDE) [1] GA-PCNN [31], AUTO [14]. The segmentation result is shown in Figure 4. This algorithm is run in Intel Core i5-63002.30 ghz CUP, 8GB of memory computer, and MATLAB Software 2021B environment.

4.2. Performance Evaluation Parameters

The final quality of image segmentation needs not only to be measured by visual effect, but also to be judged by objective evaluation coefficient. In order to more comprehensively verify the segmentation effect and generality of the improved algorithm and fitness function, this paper numerically quantizes the images of Berkeley segmentation dataset with the help of the following performance evaluation parameters [22]. The final quality of image segmentation needs not only to be measured by visual effect, but also to be judged by objective evaluation coefficient. In order to more comprehensively verify the segmentation effect and generality of the improved algorithm and fitness function, this paper numerically quantizes the images of Berkeley segmentation dataset with the help of the following performance evaluation parameters.

1 Regional consistency (*UM*)

Region consistency refers to the consistency of attributes in the same region after image segmentation. Its formula is as follows:

$$\mu_n = \sum_{(i,j)\in R_i} \frac{f(i,j)}{B_n} \tag{19}$$

$$\sigma_n^2 = \sum_{(i,j)\in R_i} \left[f(i,j) - \mu_n\right]^2 \tag{20}$$

$$UM = 1 - \frac{\left(\sigma_1^2 + \sigma_2^2\right)}{A} \tag{21}$$

Where, f is the image gray value, BN is the total number of pixels in the corresponding region after segmentation, and a is the normalization factor, that is, the sum of pixels. The larger the regional consistency parameter um, the better the image segmentation effect.

2 Color difference mean comparison (*CM*)

CM displays the contrast difference between the background average value and the target pixel. Image segmentation divides the image into non overlapping regions, and the attributes between different regions have obvious differences. Therefore, in image binary segmentation, the greater the contrast between the foreground target and the background region, the better the image segmentation effect. The expression is as follows:

$$CM = \frac{\left|\mu_1 - \mu_2\right|}{\mu_1 + \mu_2}. \tag{22}$$

Among them, $\mu1$ and $\mu2$ represents the gray expected mean of the foreground target and background area after image segmentation. Theoretically, the better the segmentation effect, the greater the color difference between the target and the pixels in the background area, the greater the color difference between the pixels in the class, that is, when the mean contrast of the color difference is the largest, the segmentation result is the overall best segmentation result.

Finally, in this paper, information entropy IE, compactness CPS, regional consistency um and color difference mean comparison cm are used as the performance evaluation parameters of segmented images. The obtained values are shown in Table 1 and the statistical histogram is shown in Figures 4-7.

In Table 1, F1-F7 respectively correspond to the previous images 1-7. Four different segmentation algorithms correspond to four different sets of parameter calculation results. A total of 4 * 4 * 7 = 112 different parameter values can be obtained. In Fig. 5, (a) represents *IE* parameter values of different algorithms, (b) represents *CPS* parameter, (c) represents *CM* parameter, and (d) represents *UM* parameter. From the performance evaluation parameter histograms in Table 1 and Figure 5, it can be seen that the values of some performance evaluation parameters of other methods fluctuate greatly, while proposed algorithm performs well in the segmentation of multiple different kinds of pictures, and there will not be too small or too large differences.

Because there are many segmented pictures and the segmentation performance indicators of each picture are complex, it will have a great impact on the later evaluation. Therefore, in order to facilitate the overall comparison of data, this paper normalizes the obtained evaluation coefficients to obtain Table 2.

Figure 5
Image performance evaluation parameter

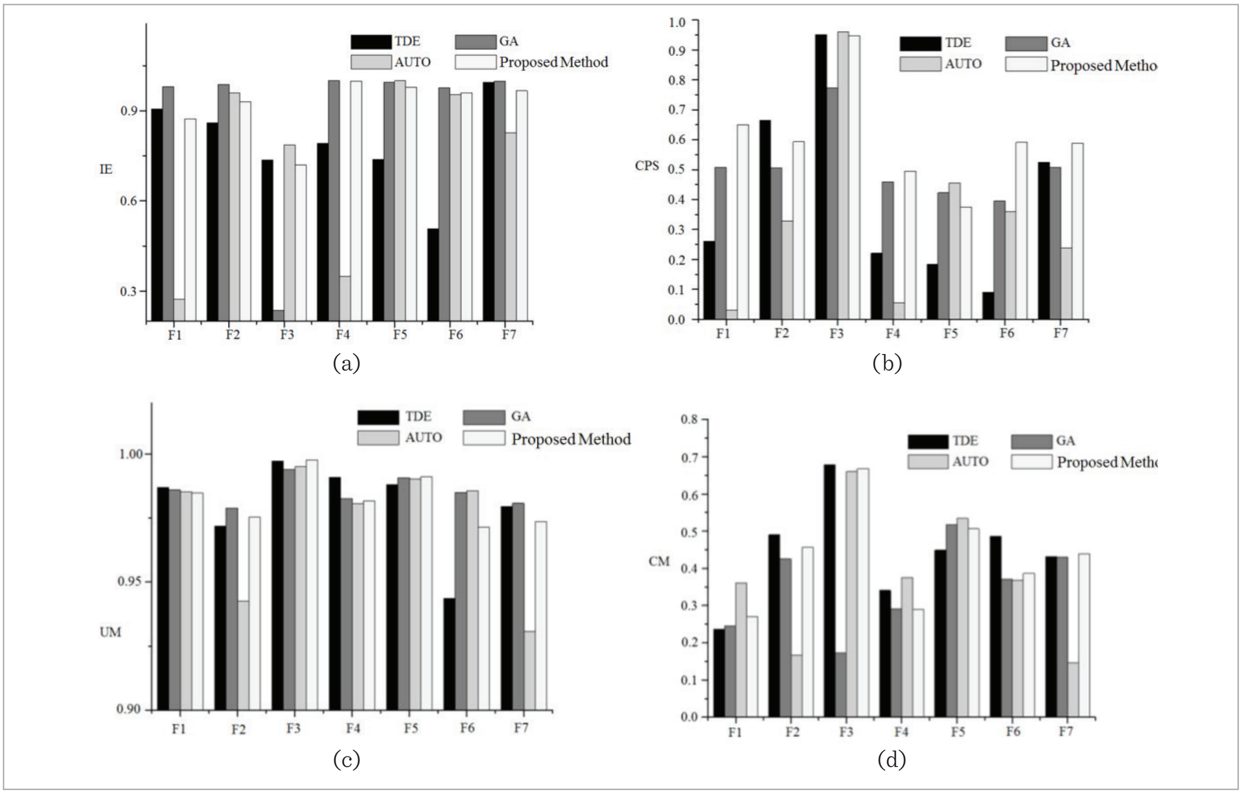


Table 1
Evaluation index of image segmentation effect

	Evaluation parameters	F1	F2	F3	F4	F5	F6	F7	Overall evaluation
TDE	*E*	0.9054	0.8598	0.7372	0.7924	0.7382	0.5084	0.9949	5.5363
	CPS	0.2609	0.6647	0.9514	0.2208	0.1831	0.0897	0.5249	2.8955
	UM	0.9869	0.9718	0.9972	0.9909	0.988	0.9436	0.9796	6.8580
	CM	0.2367	0.4902	0.679	0.3408	0.4487	0.4865	0.4319	3.1138
GA	*IE*	0.9801	0.9873	0.2371	0.9997	0.9949	0.9769	0.9981	6.1741
	CPS	0.5085	0.5057	0.7735	0.4598	0.4228	0.3955	0.5075	3.5733
	UM	0.986	0.9789	0.9939	0.9827	0.9907	0.9851	0.9808	6.8981
	CM	0.2459	0.4252	0.1730	0.2907	0.5178	0.3707	0.4298	2.4531
AUTO	*IE*	0.2741	0.9591	0.7866	0.3489	0.9999	0.954	0.8264	5.1490
	CPS	0.0307	0.3284	0.9608	0.0547	0.4559	0.3598	0.239	2.4293
	UM	0.9853	0.9425	0.9951	0.9806	0.9903	0.9857	0.9308	6.8103
	CM	0.3607	0.1669	0.6601	0.3746	0.5342	0.3682	0.1467	2.6114
Proposed Method	*E*	0.8734	0.9307	0.7192	0.9984	0.9791	0.9601	0.9667	6.4276
	CPS	0.6507	0.5929	0.9468	0.4947	0.3750	0.5912	0.5891	4.2404
	UM	0.9848	0.9753	0.9978	0.9818	0.9911	0.9714	0.9736	6.8758
	CM	0.2709	0.4574	0.6681	0.2894	0.5062	0.3865	0.4390	3.0175

Table 2
Normalization of image segmentation effect evaluation index

	CM	CPS	UM	IE	Normalized value
TDE	3.1138	2.8955	6.858	5.5363	0.8846
GA	2.4531	3.5733	6.8981	6.1741	0.8978
AUTO	2.6114	2.4293	6.8103	5.149	0.8000
Proposed	3.0175	4.2404	6.5758	6.4276	0.9806

From the normalized value, it can be seen that the segmentation effect of proposed algorithm is 10.85% higher than that of TDE algorithm, 9.22% higher than that of GA algorithm, and 22.58% higher than that of auto algorithm.

5. Conclusions

Aiming at the problems that there are many parameters in the pulse coupled neural network model and it is not easy to select automatically, and the segmentation effect needs to be observed and evaluated manually, an image segmentation method combined with adaptive glowworm algorithm is proposed, and a new weighted fitness function is given. In order to verify the advantages and disadvantages of the algorithm, seven gray images in Berkeley segmentation data set are segmented. From the segmented images obtained from the experiment, it can be seen that the algorithm proposed in this paper retains the image details better when separating the target and background, and performs best in visual effect compared with other algorithms. In the quantization results, by comparing the segmentation evaluation parameters of different algorithms, it can be found that the overall performance of this algorithm is better than other algorithms. However, the algorithm also has shortcomings in the experimental process. Because PCNN network needs to traverse and scan the image for many times, and the glowworm swarm intelligent algorithm is introduced to randomly set parameters, the complexity of the algorithm is greatly improved. Therefore, how to effectively reduce the time complexity of the algorithm is the direction of further research.

Acknowledgement

This paper is supported by Department of Science and Technology of Jilin Province (20220203091SF).

Data Sharing Agreement

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, author-ship, and/or publication of this article.

References

1. Brink, A. D. Thresholding of Digital Images Using Two-Dimensional Entropies. Pattern Recognition, 1992, 25(8), 803-808. https://doi.org/10.1016/0031-3203(92)90034-G
2. Chen, Y., Park, S. K., Ma, Y., Ala, R. A New Automatic Parameter Setting Method of a Simplified PCNN for Image Segmentation. IEEE Transactions on Neural Networks, 22(2011), 880-892. https://doi.org/10.1109 / TNN.2011.2128880
3. Eckhorn, R., Reitboeck, H. J., Arndt, M., Dicke, P. Feature Linking via Synchronization Among Distributed Assemblies: Simulations of Results from Cat Visual Cortex. Neural Computing, 1990, 2(3), 293-307. https://doi.org/10.1162/neco.1990.2.3.293
4. Ghosh, S., Das, N., Das, I., et al. Understanding Deep Learning Techniques for Image Segmentation. ACM Computing Surveys (CSUR), 2019, 52(4), 73. https://doi.org/10.1145/3329784
5. Guo, Y.-C., Jiang, F., Gong, X. A Segmentation Method of Color Blindness Detection Image Based on Simplified PCNN. Journal of Anhui University (Natural Science Edition), 2013, 1.

6. He, F., Fu, C., Shao, H., et al. An Image Segmentation Algorithm Based on Double-Layer Pulse-Coupled Neural Network Model for Kiwifruit Detection. Computers & Electrical Engineering, 2019, 79, 106466. https://doi.org/10.1016/j.compeleceng.2019.106466
7. He, F., Guo, Y., Gao, C. A Parameter Estimation Method of the Simple PCNN Model for Infrared Human Segmentation. Optics & Laser Technology, 2019, 110, 114-119. https://doi.org/10.1016/j.optlastec.2018.05.042
8. Ho, T. W., Qi, H., Lai, F., et al. Brain Tumor Segmentation Using U-Net and Edge Contour Enhancement. Proceedings of the 2019 3rd International Conference on Digital Signal Processing. ACM, 2019, 75-79. https://doi.org/10.1145/3316551.3316554
9. Jiao, K., Xu, P., Zhao, S. A Novel Automatic Parameter Setting Method of PCNN for Image Segmentation. Proceedings of the 2018 IEEE 3rd International Conference on Signal and Image Processing (ICSIP), 2018, 265-270. https://doi.org/10.1109/SIPROCESS.2018.8600474
10. Khorram, B., Yazdi, M. A New Optimized Thresholding Method Using Ant Colony Algorithm for MR Brain Image Segmentation. Journal of Digital Imaging, 2019, 32(1), 162-174. https://doi.org/10.1007/s10278-018-0111-x
11. Krishnanand, K. N., Ghose, D. Glowworm Swarm Optimization for Simultaneous Capture of Multiple Local Optima of Multimodal Functions. Swarm Intelligence, 2009, 3(2), 87-124. https://doi.org/10.1007/s11721-008-0021-5
12. Kullback, S. Information Theory and Statistics. Courier Corporation, 1997.
13. Li, C. H., Lee, C. K. Minimum Cross Entropy Thresholding. Pattern Recognition, 26(4), 617-625. https://doi.org/10.1016/0031-3203(93)90115-D
14. Lian, J., Shi, B., Li, M., et al. An Automatic Segmentation Method of a Parameter-Adaptive PCNN for Medical Images. International Journal of Computer Assisted Radiology and Surgery, 2017, 12(9), 1511-1519. https://doi.org/10.1007/s11548-017-1597-2
15. Liang, P., Sun, G., Wei, S. Application of Deep Learning Algorithm in Cervical Cancer MRI Image Segmentation Based on Wireless Sensor. Journal of Medical Systems, 2019, 43(6), 156. https://doi.org/10.1007/s10916-019-1284-7
16. Mao, X., He, L. F., Wang, Q. P. Multilevel Color Image Segmentation Based on Improved Glowworm Swarm Optimization Algorithm. Computer Science, 2017, 44(S1), 206-211.
17. Pal, N. R., Pal, S. K. A Review on Image Segmentation Techniques. Pattern Recognition, 1993, 26(9), 1277-1294. https://doi.org/10.1016/0031-3203(93)90135-J
18. Ranganath, H. S., Kuntimad, G., Johnson, J. L. Pulse Coupled Neural Networks for Image Processing. Proceedings IEEE Southeastcon '95. Visualize the Future, IEEE, 1995, 37-43.
19. Reza, A., Ramin, H., Koorush, Z. A Multi-Objective Artificial Bee Colony Algorithm. Swarm and Evolutionary Computation, 2012, 2(1), 39-52. https://doi.org/10.1016/j.swevo.2011.08.001
20. Sander, J., de Vos, B. D., Wolterink, J. M., et al. Towards Increased Trustworthiness of Deep Learning Segmentation Methods on Cardiac MRI. In Medical Imaging 2019: Image Processing. International Society for Optics and Photonics, 2019, 10949, 1094919. https://doi.org/10.1117/12.2511699
21. Song, Z., Jiang, H., Li, S. A Novel Fusion Framework Based on Adaptive PCNN in NSCT Domain for Whole-Body PET and CT Images. Comput. Math. Methods Med., 2017. https://doi.org/10.1155/2017/8407019
22. Wang, A. W., Song, Y. J. Image Segmentation Based on Pulse Coupled Neural Network. Computer Science, 2017, 44(04), 317-322.
23. Wang, G., Li, W., Zuluaga, M. A., et al. Interactive Medical Image Segmentation Using Deep Learning with Image-Specific Fine Tuning. IEEE Transactions on Medical Imaging, 2018, 37(7), 1562-1573. https://doi.org/10.1109/TMI.2018.2791721
24. Wang, L., Chen, G., Shi, D., et al. Active Contours Driven by Edge Entropy Fitting Energy for Image Segmentation. Signal Processing, 2018, 149, 27-35. https://doi.org/10.1016/j.sigpro.2018.02.025
25. Wen, C. J., Wang, S. S., Yu, H. L., et al. Image Segmentation Method for Maize Diseases Based on Pulse Coupled Neural Network with Modified Artificial Bee Algorithm. Transactions of the Chinese Society of Agricultural Engineering, 2013, 29(13), 142-149.
26. Xiao, L., Ouyang, H., Fan, C., et al. Gesture Image Segmentation with Otsu's Method Based on Noise Adaptive Angle Threshold. Multimedia Tools and Applications, 2020, 79, 35619-35640. https://doi.org/10.1007/s11042-019-08544-7
27. Xiaodong, G., Daoheng, Y., Zhang, L. Image Shadow Removal Using Pulse Coupled Neural Network. IEEE Trans Neural Netw, 2005, 16(3), 692-698. https://doi.org/10.1109/TNN.2005.844902

28. Yang, X. S. Glowworm Algorithms for Multimodal Optimization. Mathematics, 2009, 5792, 169-178. https://doi.org/10.1007/978-3-642-04944-6_14
29. Yang, Z., Dong, M., Guo, Y., Gao, X., Wang, K., Shi, B. A New Method of Micro-Calcifications Detection in Digitized Mammograms Based on Improved Simplified PCNN. Neurocomputing, 218(2016), 79-90. https://doi.org/10.1016/j.neucom.2016.08.068
30. Yang, Z., Lian, J., Li, S., Guo, Y., Qi, Y., Ma, Y. Heterogeneous SPCNN and Its Application in Image Segmentation. Neurocomputing, 2018. https://doi.org/10.1016/j.neucom.2018.01.044
31. Zhang, D., Mabu, S., Hirasawa, K. Image Denoising Using Pulse Coupled Neural Network with an Adaptive Pareto Genetic Algorithm. IEEJ Transactions on Electrical and Electronic Engineering, 2011, 6(5), 474-482. https://doi.org/10.1002/tee.20684
32. Zhang, K. H., Tan, Z. H., Li, B. Automated Image Segmentation Based on Pulse Coupled Neural Network with Particle Swarm Optimization and Comprehensive Evaluation. Optics and Precision Engineering, 2018, 26(04), 962-970. https://doi.org/10.3788/OPE.20182604.0962
33. Zhang, M., Wang, S. R., Guo, X. Y., et al. Image Segmentation Method for Potato Diseases Based on Pulse Coupled Neural Network with Shuffle Frog Leap Algorithm. Journal of Plant Protection, 2018, 45(02), 322-331.
34. Zhao, C., Zhang, H., Yan, Y., et al. Remote Sensing Image Fusion Based on Adaptive Pulse Coupled Neural Network (PCNN) in Firefly Optimization. Journal of Harbin Engineering University, 2019, 40(3), 501-508.
35. Zhao, D., Liu, L., Yu, F., et al. Ant Colony Optimization with Horizontal and Vertical Crossover Search: Fundamental Visions for Multi-Threshold Image Segmentation. Expert Systems with Applications, 2021, 167, 114122. https://doi.org/10.1016/j.eswa.2020.114122