Journal of Advances in Artificial Life Robotics
Vol. 4(1); June (2023), pp. 20–26
ON LINE ISSN 2435-8061; ISSN-L 2435-8061
https://alife-robotics.org/jallr.html

Research Article

Design and Application of Enhanced Grey Wolf Optimization-based Support Vector Machine

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ARTICLE INFO

Article History
Received 10 October 2022
Accepted 31 August 2023

Keywords
Apple external quality assessment
Enhanced Grey wolf optimization arithmetic IGWO
Support vector machine
Reference function
IGWO-SVM

ABSTRACT

An enhanced variant of the Grey Wolf Optimization (GWO) algorithm, known as the Improved Grey Wolf Optimization (IGWO), was introduced with the primary objective of improving the precision of apple's external quality assessment categorization using Support Vector Machine (SVM) as the underlying classifier.The IGWO algorithm incorporates several enhancements, including the utilization of Logistic chaos mapping, a nonlinear convergence factor, and Cauchy variation. Initially, diverse benchmark functions were employed to assess the efficacy of the IGWO methodology. The experimental outcomes demonstrated that the IGWO method significantly enhanced both the rate of convergence and precision. Subsequently, an image processing approach was employed to capture the exogenous characteristics of apples, which were then utilized as the dataset. The IGWO method was employed to fine-tune the regularization parameters and kernel parameters in the SVM, resulting in the optimal IGWO-SVM classification model. Finally, a comparative analysis was conducted between the classification results obtained from SVM, GMO-SVM, and IGWO-SVM. The findings revealed that the IGWO-SVM model achieved the peak accurate classification performance, surpassing the other methods.

1. Introduction

Apples are the fruit with the largest planted area in China, making it an important fruit industry. However, if the quality is uneven, it cannot be advanced. Currently, apple classification is mainly done manually. However, this approach is based on individual subjectivity, and is characterized by reduced classification efficiency and limited classification accuracy. Therefore, adopting effective scientific and technical methods for apple classification is of great importance and value in research. In the agricultural field, there has been remarkable progress and development in image processing technology and machine vision, and their use is remarkable. Li [1] introduced a multi-feature integration approach with a decision-integration method for apple classification using D-S evidence theory and achieved an impressive accuracy rate of 92.5%. Liang [2] targeted the classification of wheat grains, extracted the characteristics of wheat grains by digital image processing, and used hierarchical classification method and membership function method to classify wheat grains with his 93% accuracy. Lee et al. [3] used image processing techniques to extract the features of apples through computer vision technology. They then applied a backpropagation artificial neural network for accurate classification and achieved a remarkable classification accuracy of 92.5%. Xiaqing et al. [4] utilized an improved algorithm of particle swarm optimization to train a least squares support vector machine (LS-SVM) for apple classification. Experimental results showed him an amazing accuracy of over 96% in classifying apples. Li Xujun et al. [5] introduced a new apple classification algorithm that integrates a discriminant tree Analysis with an enhanced decision-making approach using

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support vector machines (SVM). The results demonstrated the feasibility, with classification accuracy greater than 98%. These results highlight that the proposed approach is effectively applicable to apple classification. Zhao Liping et al. [6] proposed an apple classification method that combines wavelets and fuzzy algorithms, and the classification accuracy of the algorithm reached over 97% in three stages of apple classification, indicating that this algorithm can be used for apple classification detection. certified. Li Wenqi et al. [7] presented a convolutional neural network based apple classification algorithm. Using the DF model he classified three grades of apples and showed a classification accuracy of 97%. He Jinrong et al. [8] proposed his DXNet model for apple appearance classification based on deep learning. Experimental results reveal that the classification accuracy of the proposed algorithm is 97.84%. This paper, based on previous work, addresses the challenge of poor apple classification accuracy when using support vector machines (SVMs), improves his IGWO with the aim of increasing apple classification accuracy, and uses support vectors Optimized machine (SVM) parameters.

Analysis with an enhanced decision-making approach using support vector machines (SVM). The results demonstrated the feasibility, with classification accuracy greater than 98%. These results highlight that the proposed approach is effectively applicable to apple classification.

2. Standard The Canonical Algorithm of Grey Wolf Optimization

The Grey Wolf Optimization (GWO) method, as described in reference [9], is an optimization algorithm that emulates the predatory behavior of grey wolves. In this algorithm, wolves are categorized into four ranks based on their fitness values. The grey wolf exhibiting the highest fitness value is denoted as α, the runner-up wolf is β, the third- ranked wolf is δ, and the residual wolf is ω. In the process of capturing prey, the three wolves denoted as α, β and δ ach possessing the highest fitness value, will be prioritized for preying pursuits, while the remaining wolves ω will follow the first three wolves α, β and δ to attack, and the final prey position is the solution of the optimized target.

The representation of the Grey Wolf algorithm for encircling prey is depicted by Eqs. (1)-(5):

$$D = \left| C \cdot X_p(t) - X_i(t) \right| \tag{1}$$

$$X_i(t+1) = X_p(t) - A \cdot D \tag{2}$$

$$A = 2ar_1 - a \tag{3}$$

$$C = 2r_2 \tag{4}$$

$$a = 2 - \frac{2t}{t_{\max}} \tag{5}$$

The mathematical formulation for individual hunting behavior in the Grey Wolf algorithm is like Eqs: (6)-(8)

$$D_\alpha = \left| C_1 \cdot X_\alpha(t) - X_i(t) \right| \tag{6}$$

$$D_\beta = \left| C_2 \cdot X_\beta(t) - X_i(t) \right| \tag{7}$$

$$D_\delta = \left| C_3 \cdot X_\delta(t) - X_i(t) \right| \tag{8}$$

in the equation, D_α, D_β and D_δ denote the distances between the individuals α, β and δ respectively. $X_\alpha(t)$, $X_\beta(t)$ and $X_\delta(t)$ depict the prevailing coordinates of α, β, and δ correspondingly; C_1, C_2, C_3 are probabilistic vectors;

$$X_1 = X_\alpha(t+1) = X_\alpha(t) - A_1 \cdot D_\alpha \tag{9}$$

$$X_2 = X_\beta(t+1) = X_\beta(t) - A_2 \cdot D_\beta \tag{10}$$

$$X_3 = X_\delta(t+1) = X_\delta(t) - A_3 \cdot D_\delta \tag{11}$$

$$X_i(t+1) = \frac{X_1 + X_2 + X_3}{3} \tag{12}$$

In Eqs, (9)-(11), X_1, X_2 and X_3 respectively represent the updated positions of α, β, and δ after guiding ω. In Eq. (12), $X_i(t+1)$ represents the updated position of ω, which corresponds to the optimal outcome of the offspring grey wolf progeny.

3. Improved Enhanced Grey Wolf Optimization Arithmetic

3.1. *Logistic chaos system*

In grey wolf algorithm, the initialization of grey wolf pack is generally randomly generated. This may lead to a non-uniform distribution of the population within the solution space, subsequently impacting the algorithm's convergence speed and the time required to locate the optimal solution. Logistic chaos mapping [10] is an irregular chaotic movement with the advantages of randomness and ergodicity. Incorporating Logistic chaotic mapping as a substitute for Stochastic initialization in the Grey Wolf algorithm enhances the uniform dispersion of the initial population, thereby augmenting the algorithm's capacity for global search. The equation denoting the Logistic chaos mapping is presented as Eq. (13):

$$X_{n+1} = X_n \times \mu \times (1 - X_n), \mu \in [0,4], X \in [0,1] \tag{13}$$

3.2. *Enhancement of the nonlinear convergence factor*

Within the Graywolf algorithm, the convergence factor linearly decreases within the range of [0, 2]. However, in the enhanced Grey Wolf algorithm, a nonlinear convergence factor is employed, as exemplified by Eq. (14), to augment the algorithm's search capability. The improved convergence factor progressively decreases in a linear fashion as the amount of iterations increases from 0 to 2. As depicted in Fig.1, during the initial iterations, the enhanced astringent factor exhibits a decreased convergence rate when compared to the original algorithm. This modification aims to facilitate the identification of the optimal solution across the entire search space. Towards the end of the iteration process, the convergence factor accelerates, leading to an increased rate of convergence. This acceleration enhances the accuracy of searching for local optimal solutions.

$$a = 2 - 2\left(\frac{1}{e-1} \times \left(e^{\frac{t}{t_{\max}}} - 1\right)\right) \tag{14}$$

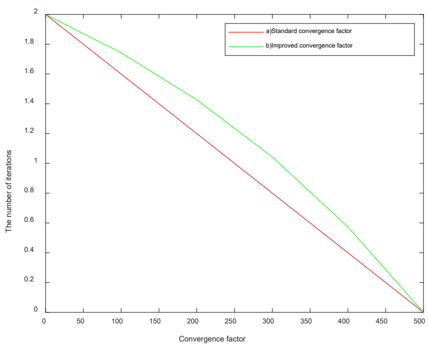


Fig. 1 Nonlinear convergence coefficient

3.3. *Introduction of Cauchy Perturbation*

During the Quest for the optimal solution in the Grey Wolf algorithm, individuals within the population gradually converge towards individuals with superior fitness as the iteration count increases. This phenomenon results in a reduction in population diversity, potentially causing the algorithm to become trapped in local optima. To mitigate the risk of the algorithm getting trapped in local optima, the improved Grey Wolf algorithm incorporates Cauchy variation [11]. And the Cauchy distribution features are: Ends with a long tail, this distribution makes individuals have a higher probability of jumping to a better position, jump out of local optimal, zero the center peak is small, smooth from the trend of the peak dropped to zero for the current generation of the optimal solution of Cauchy mutation, increase species diversity and richness, improve the understanding of the search space and improve the algorithm's propensity to escape local optima solution of probability, The variation formula is expressed as Eq. (15) in the algorithm.

$$X(\varphi+1) = X_{\text{best}}(\varphi) + C(0,1) \oplus X_{\text{best}}(\varphi) \tag{15}$$

where, $X_{\text{best}}(\varphi)$ is the global optimal of generation φ;The value $C(0,1)$ corresponds to the standard Cauchy distribution.

3.4. *Algorithm implementation process*

The improved Grey Wolf algorithm follows the following steps:

(i) Algorithm parameter setting: set the count of wolves N, the parameters to consider include the dimensionality of the exploration domain (D), the upper limit of iteration cycles (Max), and the upper and lower limits of the exploration domain.

(ii) Initial population: The initial population is generated using Logistic chaos mapping, ensuring a uniform distribution.;

(iii) The fitness function of each wolf was evaluated, and the grey wolf with the highest fitness value was identified as α, the second-ranking wolf was β, the third-ranking wolf was δ, and the remaining individual of the wolf population was ω. The corresponding positions X_α, X_β and X_δ were determined;

(iv) According to Eq. (15), cauchy variation is performed on the placement of the optimal grey wolf individual in the current wolf pack;

(v) In accordance with the nonlinear convergence factor introduced within this research, the parameters are calculated, and the values of A and C are calculated according to Eq. (3) and (4);

(vi) According to Eqs. (6)-(8), the individual positions of the population are updated, the fitness is recalculated, and the values of α, β and δ are updated;

(vii) Verify if the iteration count has reached its upper limit.If the condition is met, terminate the iteration process and output the optimal solution. Otherwise, return (iii) and continue to next;

3.5. *Improved grey Wolf algorithm test*

In order to validate the effectiveness of the proposed methodology, a comprehensive comparative study is performed in comparison with the conventional Grey Wolf algorithm. Four standardized evaluation functions are selected for conducting simulation experiments. Table 1 presents the details of the standard test functions used in the experiments. Among these attributes, F1 and F2 exhibit unimodal characteristics, whereas F3 and F4 demonstrate multimodal attributes. The experimental setup involved an Intel(R) Core(TM) i5-8300H CPU @ 2.30GHz processor, 16GB of RAM, and Matlab2018b software.

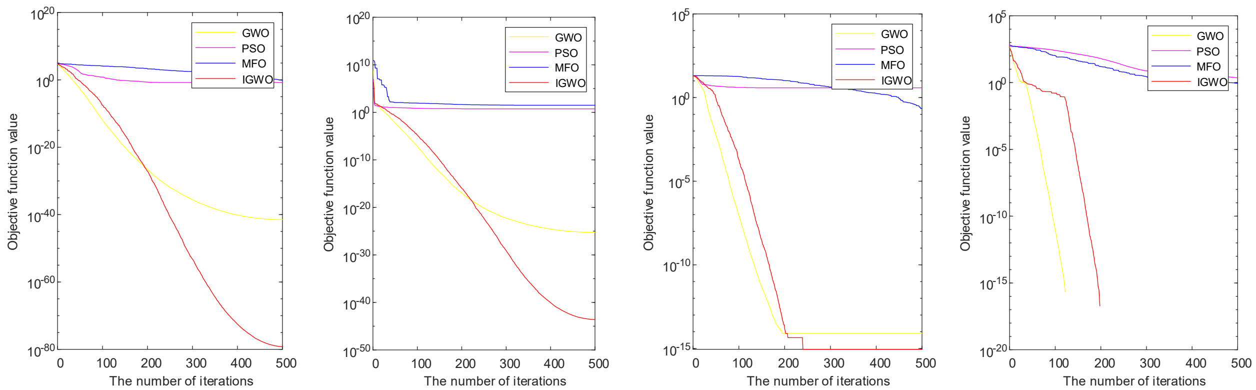
Table 1 Benchmark function

Capability name	Capability formula	Dim.	Realm
Spheroidal	$f_1(x)=\sum_{i=1}^{n} X_i^{2}$	30	[-100,100]
Schwefel2.22	$f_2(x)=\sum_{i=1}^{n}\lvert x_i\rvert+\prod_{i=1}^{n}\lvert x_i\rvert$	30	[-10,10]
Ackley	$f_9(x)=-20\exp(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i^{2}})-\exp(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)+$	30	[-32,32]
Griewank	$f_{10}(x)=\frac{1}{4000}\sum_{i=1}^{n}x_i^{2}-\prod_{i=1}^{n}\cos\frac{x_i}{\sqrt{i}}+1$	30	[-600,600]

Average value and standard deviation are used to test the performance of the algorithm. Average value can reflect the accuracy achieved by the algorithm. The standard deviation can serve as an indicator of the arithmetic 's stability. It measures the dispersion or variability of the algorithm's performance. Table 2 presents the experimental results, while Fig. 2 displays the convergence curve. In terms of both unimodal functions F1 and F2, as well as multimodal functions F3 and F4, the Improved Grey Wolf Optimization (IGWO) algorithm consistently outperforms other algorithms such as Particle Swarm Optimization (PSO) [12], Moth Flame Optimization (MFO) [13], and standard Grey Wolf Optimization (GWO) in terms of performance.

Table 2 Comparative analysis of outcomes from various algorithms

Function	PSO		MFO		GWO		IGWO	
	AVE	STD	AVE	STD	AVE	STD	AVE	STD
F1	3.14e-2	9.44e-2	3.57e-3	2.31e-3	4.19e-23	1.02e-22	8.21e-41	2.28e-41
F2	2.00e-3	2.67e-3	1.88e-3	6.85e-3	3.12e-28	2.34e-27	7.85e-47	8.72e-46
F3	2.23e-1	3.02e-2	3.69e-3	5.43e-3	1.74e-16	1.02e-15	4.63e-17	2.53e-16
F4	2.72e+0	1.68e+0	6.18e-2	1.58e-2	2.94e+1	1.12e+0	1.39e-10	7.51e-10



(a) Spheroidal (b) Schwefel2.22 (c) Ackley (d) Griewank

Fig. 2 Convergence profiles of GWO, PSO, MFO, and IGWO on benchmark evaluation functions.

4. Parameter optimization of support vector machine

Support Vector Machine (SVM) [14] is a overseen classification methodology known for its efficacy in handling nonlinear classification problems. The principle of support vector machine can be simply described as follows: use the hyperplane to separate points of different categories in the data set on both sides, and ensure that the points on both sides are as far away from the points on the hyperplane as possible. The separated hyperplane is:

$$w^T x + b = 0 \tag{16}$$

In Eq. (16), w refers to the column vector that indicates the orientation of the hyperplane, while b represents the offset term denoting the distance between the hyperplane and the origin. If the data is linearly non-separable, soft interval edge is used to describe:

$$\begin{cases} \min\limits_{w,b} \frac{1}{2}\|w\|^2 + C\sum\limits_{i=1}^{m}\mu_i \\ s.t. y_i(w^T x_i + b) \geq 1 - \mu_i, \mu_i \geq 0, i = 1,2,...m \end{cases} \tag{17}$$

In Eq. (17), μ_i represents the slack variable; C is the regularization coefficient, which depicts the penalty degree of the wrong sample segmentation, and its parameter affects the precision of SVM segmentation. In order to solve the ability of support vector machine to process nonlinear data, radial basis kernel function is introduced. For Gaussian kernel function:

$$k(x, x_i) = \exp\left\{-\frac{\|x - x_i\|^2}{2\sigma^2}\right\} \tag{18}$$

In Eq. (18), σ is the kernel function optimization parameter; Selecting proper kernel function σ and parameter C has significant influence on improving the accuracy of apple classification.

5. Apple grading data set

In this paper, a total of 306 apple samples were tested, and image processing method was used to extract the size, color and roundness of apples as data sets. According to relevant literature and the requirements of national standards GB/T10651-2008 and DB21/T1426-2006, apples are divided into three grades, and the specific parameters are shown in Table 3 below: Among them, apples with fruit diameter greater than 80mm, red color accounting for more than 90%, and roundness greater than 0.85 are special fruits, and their label is set to 1. Apples with fruit diameter between 70mm and 80mm, red accounting for more than 80% and roundness between 0.8-0.85 are first-class fruits, and the grading label is set as 2. Apples with fruit diameter less than 70mm, red proportion less than 80% and roundness less than 0.8 are considered as second-class apples. Set the label to 3. First, SVM algorithm was used for classification, then GMO-SVM was used for classification, and finally, IGWO-SVM was optimized by the improved grey wolf algorithm for comparison.

Table 3 Apple grading standards

Level	Fruit diameter	Maturity	Circularity
Special	>80mm	>90%	>0.85
First class	70mm-80mm	>80%	0.8-0.85
Second-class	<70mm	<80%	<0.8

6. Results

To validate the classification capability of the proposed IGWO-SVM algorithm, a series of classification experiments were conducted, comparing it with other algorithms such as SVM, GMO-SVM. The classification results of experimental test sets are shown as follows:

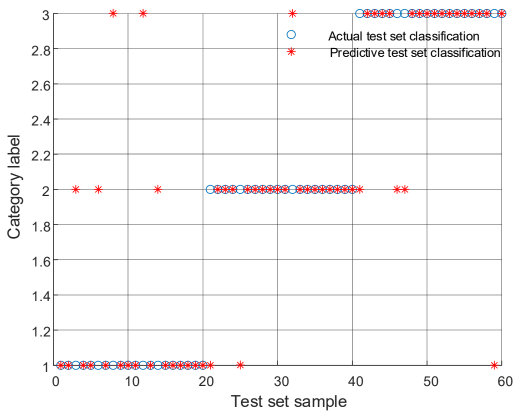


Fig.3 Results of classification using SVM

As shown in Fig. 3, the SVM algorithm without optimization achieved 49 correct classifications, resulting in a classification accuracy of 81.66%. Among them, the accuracy of characteristic fruit classification is 75%, the accuracy of first-grade fruit classification is 85%, and the accuracy of second-grade fruit classification is 85%. The classification accuracy is low. Following the optimization of the Support Vector Machine using the Grey Wolf Algorithm, the accuracy has been significantly improved. As depicted in Fig. 4, the test set demonstrates a classification accuracy of 90%. Furthermore, the accuracy for the first-class fruit category stands at 85%, while the accuracy for the second-class fruit category reaches 100% and the accuracy for the third-class fruit category reaches 85%. The appliance of the improved Grey Wolf algorithm for optimizing the Support Vector Machine (SVM) resulted in a remarkable accuracy of 98.33%, as illustrated in Fig. 5. This outcome successfully achieved the desired objective of apple classification.

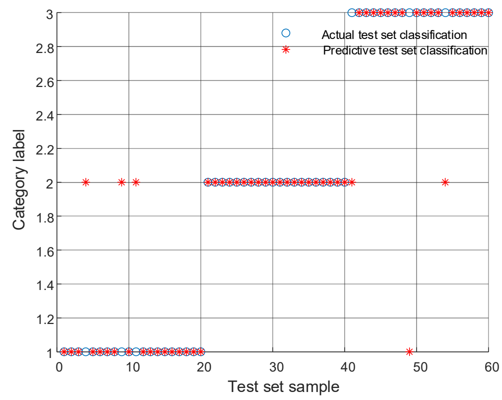


Fig.4 Results of grading using GMO-SVM

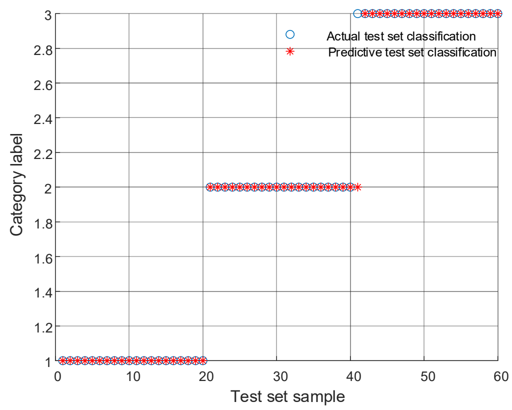


Fig.5 Results of IGWO-SVM classification

7. Conclusion

To address the limitations of slow convergence and susceptibility to local optima in the basic Grey Wolf Optimization (GWO) algorithm, this study presents an enhanced approach called the Improved Grey Wolf Optimization (IGWO) algorithm. Building upon the foundation of the GWO algorithm, the IGWO algorithm incorporates additional components, including logistic chaos mapping, a factor contributing to non-linear convergence, along with the Cauchy variation, to enhance its performance. Through comprehensive simulation experiments conducted on four benchmark evaluation functions and in comparison with the PSO, MFO, and GWO algorithms, the findings indicate that the IGWO methodology achieves significantly improved precision in enhancing the performance on the test functions. Moreover, the IGWO algorithm exhibits enhanced optimization performance in terms of robustness and capability to rapidly escape local optima.

Furthermore, the IGWO algorithm is utilized to optimize the penalty parameters and kernel parameters within the Support Vector Machine (SVM) framework, specifically tailored for apple classification. The experimental results demonstrate a remarkable accuracy rate of 98.3% for the IGWO-SVM model.

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Authors Introduction

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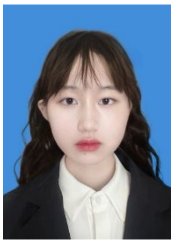

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