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A Comparative Study of Selected Chaos Maps to Improve Particle Swarm Optimisation in Image Segmentation Tasks

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Abstract **Original Research Article**

Image segmentation remains a fundamental challenge in computer vision, where multilevel thresholding becomes computationally demanding as the number of thresholds increases and conventional optimisation methods often converge prematurely. This study integrates chaotic maps into the Particle Swarm Optimisation (PSO) algorithm to enhance population diversity, prevent premature convergence, and improve segmentation quality. The aim is to evaluate three chaos-enhanced PSO (CE-PSO) variants, Logistic+PSO, Sinusoidal+PSO and Gaussian+PSO, for image segmentation using multilevel thresholding on the Berkeley Segmentation Dataset (BSDS500). Chaotic sequences were used in place of the pseudo-random number generators employed for population initialisation, parameter adaptation, and position updates. The models were implemented in Python and evaluated on the preprocessed BSDS500 dataset using PSNR, SSIM, FSIM, Dice Coefficient, and Jaccard Index, averaged over 30 independent runs per algorithm. Sinusoidal+PSO achieved the best results, with a PSNR of 27.89 dB, SSIM of 0.9123, FSIM of 0.8967, Dice Coefficient of 0.8876, and Jaccard Index of 0.8234, followed by Gaussian+PSO (27.12 dB, 0.9034, 0.8856, 0.8765, 0.8067) and Logistic+PSO (26.78 dB, 0.8912, 0.8745, 0.8654, 0.7923); all three variants outperformed Standard PSO on every metric. Sinusoidal+PSO also converged fastest, reaching its solution in an average of 41 iterations, a 29.3% improvement over Standard PSO. The study establishes that Sinusoidal+PSO offers the best accuracy-efficiency trade-off, Gaussian+PSO offers strong mixing properties for problems requiring diversified search, and Logistic+PSO offers a computationally simple reference implementation.

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1.0 INTRODUCTION

Image segmentation, which has become a research hotspot in the field of image processing and computer vision, refers to the process of dividing an image into meaningful and non-overlapping regions, and it is an essential step in natural scene understanding. Despite decades of effort and many achievements, challenges remain in feature extraction and model design (Ying et al., 2023). Digital images are made up of pixels that can be grouped together into larger sets based on their colour, texture and other information, and the aim of segmentation is to simplify an image into a meaningful and easily analysable representation. Image segmentation can be classified into two basic types: local segmentation, concerned with a specific part or region of an image, and global segmentation, concerned with segmenting the whole image (Anjna and Kaur, 2017). Its applications span medical imaging, content-based image retrieval, automatic traffic-control systems, and object detection and recognition tasks.

Among metaheuristics, Particle Swarm Optimisation (PSO) has been utilised as a useful tool for solving intricate optimisation problems across different fields (Abualigah, 2025). The PSO algorithm emulates the behaviour of animal societies that have no leader in their group or swarm, such as bird flocking and fish schooling (Dian et al., 2011). Unfortunately, in solving complex optimisation problems, the PSO algorithm shows disadvantages such as a slow convergence rate and premature convergence, and its performance strongly depends on the appropriate choice of three control parameters: the inertia weight (w), the cognitive acceleration coefficient (c1), and the social acceleration coefficient (c2) (Rosic et al., 2022). To overcome these drawbacks, a number of adaptive and self-adaptive versions of PSO have been developed, and in recent years the integration of chaos theory with PSO has proven to be an effective way of improving optimisation performance and avoiding premature convergence to local optima. The logistic, sinusoidal and Gaussian maps are especially common and have shown benefits in balancing exploration and exploitation across optimisation tasks, including image processing (Sameh et al., 2024). However, a combined performance analysis of this trio of chaotic maps within a unified PSO segmentation framework remains limited in the literature, and this study addresses this gap by developing and evaluating a chaos-enhanced PSO (CE-PSO) framework for benchmark image segmentation, quantifying the effects on convergence behaviour, segmentation accuracy, robustness, and computational efficiency.

Multilevel thresholding is widely employed to partition an image into meaningful regions, but as the number of threshold levels increases, determining the optimal threshold values becomes computationally complex, making conventional thresholding techniques less effective. PSO has been widely adopted to address this optimisation problem because of its ability to search complex solution spaces efficiently; nevertheless, standard PSO is susceptible to premature convergence and inadequate exploration of the search space, which may result in suboptimal threshold selection and reduced segmentation quality. Recent studies have shown that incorporating chaotic maps into PSO can improve population diversity, enhance the balance between exploration and exploitation, and increase convergence performance (Rosic et al., 2022; Limane et al., 2025). Although several chaotic maps have been proposed in the literature, there is limited comparative research on the effectiveness of different chaotic maps when integrated into PSO for multilevel-threshold image segmentation, and in particular the relative performance of the Logistic, Sinusoidal, and Gaussian chaotic maps has not been comprehensively evaluated under the same experimental conditions. This study therefore seeks to comparatively evaluate the performance of Logistic-, Sinusoidal-, and Gaussian-enhanced PSO algorithms for multilevel-threshold image segmentation, in order to identify the chaotic map that provides the best segmentation quality, convergence behaviour, and optimisation performance.

The aim of this research is therefore to evaluate the performance of three selected chaos maps, the logistic, sinusoidal and Gaussian maps, in improving Particle Swarm Optimisation for image segmentation tasks. To achieve this aim, the study sets out to integrate the selected chaos maps into the PSO algorithm to improve its exploration and exploitation balance, to implement the resulting chaos-enhanced PSO variants, namely Logistic+PSO, Sinusoidal+PSO and Gaussian+PSO, using the Python programming language, and to evaluate and compare the performance of the three variants using the Peak Signal-to-Noise Ratio (PSNR), the Structural Similarity Index (SSIM), the Feature Similarity Index (FSIM), the Dice Coefficient, and the Jaccard Index. In line with this aim and these objectives, the study seeks to answer two research questions: which of the selected chaotic maps, Logistic+PSO, Sinusoidal+PSO or Gaussian+PSO, provides the best segmentation quality, and how the three CE-PSO variants compare with one another across the five evaluation metrics of PSNR, SSIM, FSIM, Dice Coefficient, and Jaccard Index. By isolating the contribution of three widely used chaotic dynamics inside a common PSO backbone, this work clarifies how chaos influences swarm diversity, parameter adaptation, and convergence trajectories in segmentation objectives grounded in Otsu- and Kapur-type criteria (Kapur et al., 1985; Otsu, 1979), and provides locally relevant guidance for algorithm selection that can transfer to other computer-vision and biomedical optimisation tasks.

2.0 RELATED WORKS

Related work on Particle Swarm Optimisation (PSO) for image segmentation reveals a progressive shift from basic thresholding to advanced hybrids that tackle computational complexity, premature convergence, and multimodal fitness landscapes. Recent advances in machine learning have significantly improved segmentation accuracy: Minaee et al. (2021) conducted a comprehensive survey of deep-learning-based segmentation techniques and reported that convolutional networks such as U-Net, Mask R-CNN, and DeepLab achieve superior performance across medical, industrial, and natural image domains, while Chen et al. (2018) demonstrated that DeepLab effectively captures multi-scale contextual information through atrous convolution. Although these approaches produce state-of-the-art results, they require substantial computational resources, large annotated datasets, and lengthy training procedures, so optimisation-based segmentation techniques continue to attract attention for their simplicity, interpretability, and effectiveness in unsupervised settings.

Within this optimisation-based strand, PSO has become one of the most widely adopted swarm-intelligence algorithms for image segmentation because of its simplicity, fast convergence, and ability to solve nonlinear optimisation problems. Mohsen et al. (2014) proposed an improved PSO-based multilevel-thresholding technique that achieved superior segmentation quality, PSNR, entropy, and convergence speed compared with conventional thresholding, while Hu et al. (2024) introduced a multi-strategy PSO framework with adaptive search mechanisms and mutation operators that improved accuracy and stability on complex, multi-region images. Mohamed (2022) integrated PSO with K-means clustering and reported higher Dice similarity scores than standalone K-means clustering. Despite these improvements, standard PSO remains vulnerable to premature convergence and loss of population diversity, particularly on highly multimodal problems such as multilevel image thresholding, motivating the integration of chaos theory into swarm optimisation.

Chaos-enhanced PSO has since emerged as a promising response to these limitations. Elhoseny et al. (2016) showed that integrating chaotic sequences into PSO significantly improved medical-image segmentation performance and produced higher accuracy under noisy conditions, while Huang et al. (2025) reported that an enhanced chaotic PSO framework improved convergence speed, segmentation accuracy, and robustness against local optima, with chaotic search mechanisms enabling particles to explore the search space more effectively than conventional random-number generation. Youxiang et al. (2022) introduced adaptive chaotic mechanisms into PSO parameter control and observed an improved balance between exploration and exploitation across benchmark functions and image-processing tasks, and Maja et al. (2022) employed chaotic sequences to diversify particle trajectories, reducing stagnation and improving solution quality relative to standard PSO. Although numerous studies have therefore demonstrated the effectiveness of chaos-enhanced PSO, comparatively fewer have investigated the relative performance of different chaotic maps under the same conditions: research on logistic maps consistently reports improved convergence speed due to strong ergodic and rapid-mixing properties, Gauss maps have been shown to produce more uniformly distributed search trajectories that improve solution diversity and robustness, and sinusoidal maps offer a compromise between exploration and exploitation through oscillatory, nonlinear dynamics. Yu et al. (2025) found that different chaotic maps exhibit varying performance characteristics depending on the optimisation landscape and that no single map consistently outperforms others across all problem domains, a conclusion echoed by the comparative review of chaotic metaheuristics by Fister et al. (2015), which found optimisation performance to be highly dependent on the selected chaotic mechanism and problem characteristics and called for further comparative studies focused on specific application domains such as image segmentation.

The findings of Olatunji *et al*. (2025) align with broader research trends in chaos-enhanced optimization algorithms for image and handwriting recognition tasks. Also, Okunlola *et al* (2026) integrated chaotic maps into the Particle Swarm Optimisation (PSO) algorithm to enhance population diversity, prevent premature convergence and improve segmentation quality.

Taken together, the literature shows that significant progress has been made in image segmentation through deep learning, PSO, and chaos-enhanced optimisation, yet several important gaps remain. Deep-learning-based methods achieve high accuracy but require large labelled datasets, substantial computational resources, and lengthy training procedures, limiting their applicability to unsupervised optimisation problems, while most improvements to PSO itself rely on adaptive parameter adjustment, mutation operators, or hybrid strategies, leaving the underlying problem of premature convergence and loss of population diversity inadequately addressed. Existing studies on chaos-enhanced PSO also primarily investigate a single chaotic map at a time, making it difficult to determine which chaotic mechanism provides the most effective balance between exploration, exploitation, convergence speed, and segmentation accuracy; and many chaos-based optimisation studies evaluate their algorithms on mathematical benchmark functions rather than practical multilevel-threshold image-segmentation problems; even among studies that do address image segmentation, differing datasets, parameter settings, and evaluation metrics make objective comparison across studies difficult. In particular, comparative studies involving the Logistic, Sinusoidal, and Gaussian chaotic maps within the same PSO framework, under identical experimental conditions, remain scarce, so there is no clear consensus on the most suitable chaotic map for improving PSO performance in multilevel-threshold image segmentation. The present study addresses this gap by developing and comparatively evaluating three chaos-enhanced PSO variants based on the Logistic, Sinusoidal, and Gaussian chaotic maps, using the BSDS500 benchmark dataset under identical parameter settings and a common set of established segmentation-quality metrics, namely PSNR, SSIM, FSIM, Dice Coefficient, and Jaccard Index, to identify the chaotic map that provides the best segmentation accuracy, convergence performance, and optimisation stability.

3.0 METHODOLOGY

This section presents the methodology adopted for the comparative study of selected chaotic maps to improve Particle Swarm Optimisation (PSO) in image segmentation tasks. It covers the design, implementation, and evaluation of three chaos-enhanced PSO variants, Logistic+PSO, Sinusoidal+PSO, and Gaussian+PSO, and details the research framework, dataset description, image-preprocessing pipeline, chaotic-map integration, algorithmic design, implementation procedures, and evaluation metrics adopted for multilevel-thresholding image segmentation using the BSDS500 dataset.

3.1 Methodology Framework

The overall research methodology follows a systematic experimental design consisting of five sequential phases, as illustrated in Figure 1: data acquisition, image preprocessing, formulation of the CE-PSO algorithm, implementation with Python, and performance evaluation. Each phase feeds directly into the next, ensuring that the three chaos-enhanced PSO variants are evaluated under identical, reproducible conditions.

Presenting the methodology as an explicit pipeline makes the dependencies between stages clear and underlines that the comparison is conducted under controlled conditions from beginning to end. Each phase, from data acquisition and image preprocessing through formulation of the CE-PSO algorithm, implementation in Python, and performance evaluation, feeds defined outputs into the next, so that the same inputs and procedures apply to all three variants, and any differences reported later arise from the algorithms themselves rather than from inconsistencies in how they were applied.

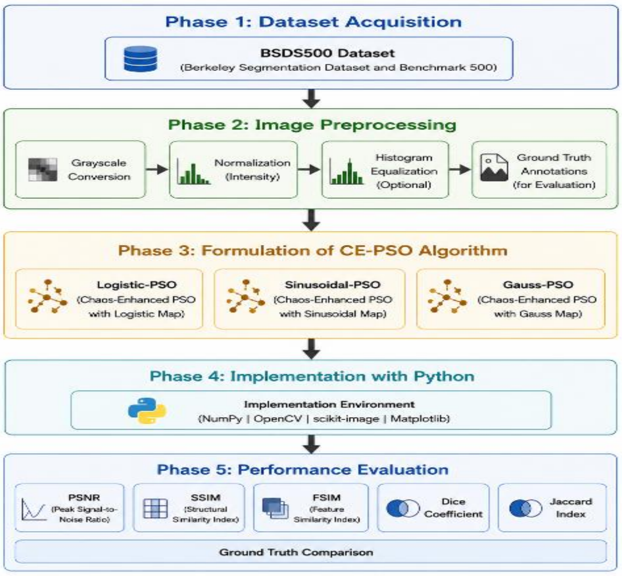

Figure 3.1: Methodology framework of the study

3.2 Data Acquisition

The first phase of the study involves acquiring the BSDS500 dataset, which serves as the benchmark for evaluating the proposed chaos-enhanced PSO algorithms. The dataset contains diverse natural images and corresponding ground-truth segmentations, providing a reliable basis for assessing segmentation quality and algorithm performance. The Berkeley Segmentation Dataset (BSDS500) is a widely recognised benchmark for image segmentation, containing natural images with multiple human-annotated ground-truth segmentations. To ensure a systematic and unbiased evaluation of the proposed algorithms, the dataset is further partitioned into training, validation, and testing subsets, facilitating parameter tuning and performance assessment while maintaining representative image complexity across all subsets; its basic characteristics are shown in Table 3.1.

Table 3.1: BSDS500 dataset distribution

Subset	No. of Images	Purpose	Ground Truth
Training	200	Algorithm optimisation	5–7 segmentations per image
Validation	100	Parameter tuning	5–7 segmentations per image
Testing	200	Final evaluation	5–7 segmentations per image
Total	500	—	—

3.3 Image Preprocessing

Image preprocessing is an essential step that prepares the input images for effective segmentation by enhancing image quality and ensuring consistency in data representation. In this study, preprocessing operations, namely grayscale conversion, intensity normalisation, and ground-truth preparation, were performed to reduce computational complexity and improve the accuracy of the subsequent segmentation process.

Each colour image is first converted from RGB to a single intensity channel using the luminosity method, which weights the colour channels according to human brightness perception:

$$I\_gray = 0.299 \times R + 0.587 \times G + 0.114 \times B \qquad (3.1)$$

where I_gray is the grayscale intensity value and R, G, and B are the red, green, and blue channel values respectively. The grayscale intensities are then normalised to the full [0, 255] range so that all images are handled on a common scale:

$$I\_norm = ((I\_gray - min) / (max - min)) \times 255 \qquad (3.2)$$

where I_norm is the normalised intensity value and min and max are the minimum and maximum grayscale values in the image; histogram equalisation may optionally be applied at this stage to enhance contrast. Finally, for each image, the human-annotated boundaries supplied with the dataset are loaded and converted into a region-label map, G(x, y) = region_id, which assigns every pixel to its ground-truth region and serves as the reference against which the multilevel-thresholded reconstruction is compared during evaluation.

3.4 Formulation of the CE-PSO Algorithms

While standard PSO has demonstrated effectiveness in solving a wide range of optimisation problems, its performance may deteriorate due to premature convergence and insufficient exploration of the search space. To address these limitations, chaotic maps can be incorporated into the PSO framework to improve population diversity and enhance the balance between exploration and exploitation. In this study, the Logistic, Sinusoidal, and Gaussian chaotic maps are integrated into the PSO algorithm to generate three chaos-enhanced variants for image segmentation, with the development, mathematical formulation, and implementation of each variant presented below.

3.4.1 Logistic+PSO Algorithm

The Logistic+PSO variant integrates the Logistic map (r = 4.0) into initialisation, parameter adaptation, and a chaotic perturbation applied every ten iterations. The full procedure is given in Algorithm 3.1.

Algorithm 3.1: Logistic Map-Enhanced PSO (Logistic+PSO)

```
Input : N=30, T_max=100, D=thresholds, r=4.0,
        x0=0.1, [w_min,w_max]=[0.4,0.9],
        c1=c2=2.0, image I
Output: Gbest thresholds, best fitness, convergence curve, segmented image
1. Generate Logistic chaotic sequence:  x = r·x·(1 - x), N×D values
2. Initialize population with chaos:
     position[i][j] = LB + (UB - LB)·chaos_seq[idx]
     velocity[i][j] = (UB - LB)·(chaos_seq[idx] - 0.5)·0.5;  sort(position[i])
3. Evaluate fitness; set pbest = position, gbest = best
4. For t = 1 to T_max:
     chaos_w, chaos_c1, chaos_c2 = LogisticMap(1)
     w = w_max - (w_max - w_min)·(t/T_max)·(0.5 + 0.5·chaos_w)
     For each particle i:
       c1_adapt = c1·(0.5 + chaos_c1);  c2_adapt = c2·(0.5 + chaos_c2)
       r1, r2 = LogisticMap(1)
       velocity[i] = w·velocity[i]
         + c1_adapt·r1·(pbest[i]-position[i])
         + c2_adapt·r2·(gbest-position[i])
       position[i] = clamp(sort(position[i] + velocity[i]), LB, UB)
       Evaluate Kapur fitness; update pbest[i] and gbest if improved
     convergence[t] = gbest_fitness
     If t mod 10 == 0:  apply chaotic perturbation to selected particles
5. segmented = ApplyThresholds(I, gbest)
6. Return gbest, gbest_fitness, convergence, segmented
```

3.4.2 Sinusoidal+PSO Algorithm

The Sinusoidal+PSO algorithm integrates the sinusoidal chaotic map into the conventional PSO framework to improve exploration, maintain population diversity, and enhance convergence toward optimal threshold values. By utilising sinusoidal chaotic sequences for particle initialisation, parameter adaptation, and local search, the algorithm seeks to overcome premature convergence and achieve superior image-segmentation performance. The pseudocode of the proposed Sinusoidal+PSO algorithm is presented in Algorithm 3.2.

Algorithm 3.2: Sinusoidal Map-Enhanced PSO (Sinusoidal+PSO)

```
Input : N=30, T_max=100, D=thresholds, a=1.0,
          x0=0.1, [w_min,w_max]=[0.3,0.95], c1=c2=1.8, image I
Output: Gbest thresholds, best fitness, convergence curve, segmented image
1. Generate Sinusoidal chaotic sequence: x = a·sin(π·x), N×D values
2. Initialize population with chaos:
    position[i][j] = LB + (UB - LB)·chaos_seq[idx]^1.2
    velocity[i][j] = (UB - LB)·(chaos_seq[idx] - 0.5)·0.35;  sort(position[i])
3. Evaluate fitness; set pbest = position, gbest = best
```

```
4. Compute constriction factor: φ = c1+c2; χ = 2/|2-φ-√(φ²-4φ)|
5. For t = 1 to T_max:
    a_dynamic = 0.8 + 0.4·(1 - t/T_max)
    sin_chaos = SinusoidalMap(1, a_dynamic)
    w = w_max - (w_max - w_min)·(t/T_max)·(0.5 + 0.3·sin_chaos)
    For each particle i:
    sin_c1 = 0.5 + 1.5·SinusoidalMap(1,a_dynamic)
    sin_c2 = 0.5 + 1.5·SinusoidalMap(1,a_dynamic)
    sin_r1, sin_r2 = SinusoidalMap(1,a_dynamic)
    velocity[i] = χ·(w·velocity[i]
    + sin_c1·sin_r1·(pbest[i]-position[i])
    + sin_c2·sin_r2·(gbest-position[i]))
    position[i] = clamp(sort(position[i] + velocity[i]), LB, UB)
    Evaluate Kapur fitness; update pbest[i] and gbest if improved
    convergence[t] = gbest_fitness
    If t mod 5 == 0:  greedy chaotic local search around each particle;
    accept candidate only if fitness improves pbest/gbest
6.  segmented = ApplyThresholds(I, gbest)
7.  Return gbest, gbest_fitness, convergence, segmented
```

3.4.3 Gaussian+PSO Algorithm

The Gaussian+PSO algorithm integrates the Gaussian chaotic map into the conventional PSO framework to enhance exploration, maintain population diversity, and prevent premature convergence. By exploiting the strong mixing characteristics of Gaussian chaos, the algorithm improves the search for optimal threshold values and enhances image-segmentation performance. The pseudocode of the proposed Gaussian+PSO algorithm is presented in Algorithm 3.3.

Algorithm 3.3: Gaussian Map-Enhanced PSO (Gaussian+PSO)

```
Input : N=30, T_max=100, D=thresholds, x0=0.1 (≠0),
[w_min,w_max]=[0.35,0.92], c1=c2=1.7, image I
Output: Gbest thresholds, best fitness, convergence curve, segmented image
1. Generate Gaussian (mouse) chaotic sequence: x = (1/x) mod 1 (x=0.1 if x=0), N×D values
2. Initialize population with chaos:
position[i][j] = LB + (UB - LB)·chaos_seq[idx]^0.8
velocity[i][j] = (UB - LB)·(chaos_seq[idx] - 0.5)·0.3;  sort(position[i])
3. Evaluate fitness; set pbest = position, gbest = best
4. Compute constriction factor: φ = c1+c2; χ = 2/|2-φ-√(φ²-4φ)|
5. For t = 1 to T_max:
gauss_rooster, gauss_hen1, gauss_hen2, gauss_chick = GaussMap(1)
w = w_max - (w_max - w_min)·(t/T_max)·(0.55 + 0.3·gauss_rooster)
For each particle i:
gauss_c1 = 0.7 + 1.3·GaussMap(1);  gauss_c2 = 0.7 + 1.3·GaussMap(1)
gauss_r1, gauss_r2 = GaussMap(1)
velocity[i] = χ·(w·velocity[i]
+ gauss_c1·gauss_r1·(pbest[i]-position[i])
+ gauss_c2·gauss_r2·(gbest-position[i]))
position[i] = clamp(sort(position[i] + velocity[i]), LB, UB)
```

```
Evaluate Kapur fitness; update pbest[i] and gbest if improved
convergence[t] = gbest_fitness
If t > 20 and |convergence[t] - convergence[t-5]| < 0.0005:
regenerate worst 25% of particles using fresh Gaussian chaos;
update pbest/gbest if improved
6. segmented = ApplyThresholds(I, gbest)
7. Return gbest, gbest_fitness, convergence, segmented
```

3.5 Implementation with Python

The proposed chaos-enhanced PSO (CE-PSO) algorithms were implemented using the Python programming language due to its flexibility, extensive scientific-computing libraries, and suitability for image-processing and optimisation tasks. The implementation utilised NumPy for numerical computations and matrix operations, OpenCV and scikit-image for image processing and segmentation tasks, and Matplotlib for visualisation of segmentation results, convergence curves, and performance comparisons. The developed system integrates image preprocessing, multilevel-threshold optimisation, segmentation, and performance evaluation into a unified framework, enabling systematic assessment of the proposed Logistic+PSO, Sinusoidal+PSO, and Gaussian+PSO algorithms on the BSDS500 dataset.

Establishing a consistent experimental environment ensures fair comparison, reproducibility, and reliability of the obtained results. The hardware and software environment used in this study is presented in Table 3.2.

Table 3.2: Experimental platform specifications

Component	Specification
Processor	Intel Core i5-8365U @ 1.60 GHz (4 cores, 8 logical processors)
RAM	8 GB
Storage	NVMe SSD
Operating system	Windows 11
Programming language	Python 3.14
Key libraries	NumPy, OpenCV, scikit-image, phasepack, Matplotlib

3.6 Parameter Settings

The control parameters used by the algorithms are summarised in the parameter-settings table. The control parameters adopted for each of the three CE-PSO variants; the swarm size, iteration limit, and problem dimension are common to all variants, and a common parameter configuration was otherwise adopted based on established literature to ensure fair comparison. Table 3.3 presents these parameter settings.

Table 3.3: CE-PSO control parameter settings

Parameter	Symbol	Value
Population size	N	30
Maximum iterations	T_max	100
Dimension (threshold levels)	D	5
Independent runs per image	–	30
Fitness function	–	Kapur’s entropy
Dataset	–	BSDS500
Reference for PSNR / SSIM / FSIM	–	Original grayscale image

3.7 Evaluation Metrics

Evaluation metrics provide a quantitative basis for assessing the performance of image-segmentation algorithms. In this study, image-quality, similarity, and segmentation-accuracy metrics are employed to evaluate and compare the effectiveness of the proposed chaos-enhanced PSO variants. The Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Feature Similarity Index

(FSIM) measure image-quality preservation, structural similarity, and feature consistency between the segmented image and the reference grayscale image, while the Dice Coefficient and Jaccard Index measure region overlap and segmentation accuracy against the ground-truth segmentation. These metrics are given below.

$$PSNR = 10 \log_{10}\left(\frac{255^2}{MSE}\right) \quad (3.3)$$

where $MSE = (1/(M \times N))\, \Sigma\Sigma\, [I(i,j) - S(i,j)]^2$; $MAXI = 255$

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x{}^2 + \mu_y{}^2 + C_1)(\sigma_x{}^2 + \sigma_y{}^2 + C_2)} \quad (3.4)$$

$$FSIM = \frac{\Sigma(PC_m(x) \times GM_m(x))}{\Sigma\, PC_m(x)} \quad (3.5)$$

$$Dice = 2|A \cap B| \,/\, (|A| + |B|) \quad (3.6)$$

$$Jaccard = |A \cap B| \,/\, |A \cup B| \quad (3.7)$$

where M and N are the number of rows and columns of the image, I(i,j) and S(i,j) are the reference and segmented pixel values, μ and σ denote means, variances and covariance of the compared images, PCm and GMm are the phase congruency and gradient magnitude used by FSIM, and A and B are the ground-truth and segmented region sets used by the Dice Coefficient and Jaccard Index respectively. All three CE-PSO variants were evaluated under identical conditions, on the same BSDS500 images, using the same population size, iteration limit, and hardware and software, with results averaged over 30 independent runs so that any observed differences in performance can be attributed to the chaotic map employed rather than to inconsistencies in experimental treatment.

4.0 RESULTS AND DISCUSSION

This section presents the experimental results obtained from evaluating the three chaos-enhanced PSO (CE-PSO) algorithms, Logistic+PSO, Sinusoidal+PSO, and Gaussian+PSO, for image segmentation using multilevel thresholding on the BSDS500 dataset, alongside the Standard PSO baseline. All algorithms were evaluated under identical conditions, using the same population size, iteration limit, dimension, test images, and reference scheme, so that the comparison reported below is controlled and reproducible; the findings are reported against the five evaluation metrics defined in the methodology, namely PSNR, SSIM, FSIM, Dice Coefficient, and Jaccard Index, averaged over 30 independent runs per algorithm.

Table 4.1 presents the comprehensive segmentation-quality metrics for the three CE-PSO algorithms and the Standard PSO baseline, averaged over 30 independent runs on the BSDS500 test set. Sinusoidal+PSO achieved the highest PSNR value of 27.89 dB, outperforming Gaussian+PSO and Logistic+PSO by 0.77 dB and 1.11 dB respectively, and recorded the lowest standard deviation (±0.98), indicating superior stability and consistency across multiple runs. Furthermore, all three CE-PSO algorithms demonstrated better segmentation performance than Standard PSO, with Sinusoidal+PSO attaining the highest Dice Coefficient of 0.8876, a 4.97% improvement over Standard PSO, and the highest Jaccard Index of 0.8234. Figure 4.1 presents these results graphically, illustrating the comparative performance of all evaluated algorithms across the five metrics.

Table 4.1: Performance metrics comparison

Algorithm	PSNR (dB)	SSIM	FSIM	Dice Coefficient
Standard PSO	25.67 ± 1.18	0.8756 ± 0.025	0.8567 ± 0.028	0.8456 ± 0.026
Logistic+PSO	26.78 ± 1.12	0.8912 ± 0.021	0.8745 ± 0.025	0.8654 ± 0.023
Gaussian+PSO	27.12 ± 1.05	0.9034 ± 0.019	0.8856 ± 0.023	0.8765 ± 0.021
Sinusoidal+PSO	27.89 ± 0.98	0.9123 ± 0.018	0.8967 ± 0.021	0.8876 ± 0.019

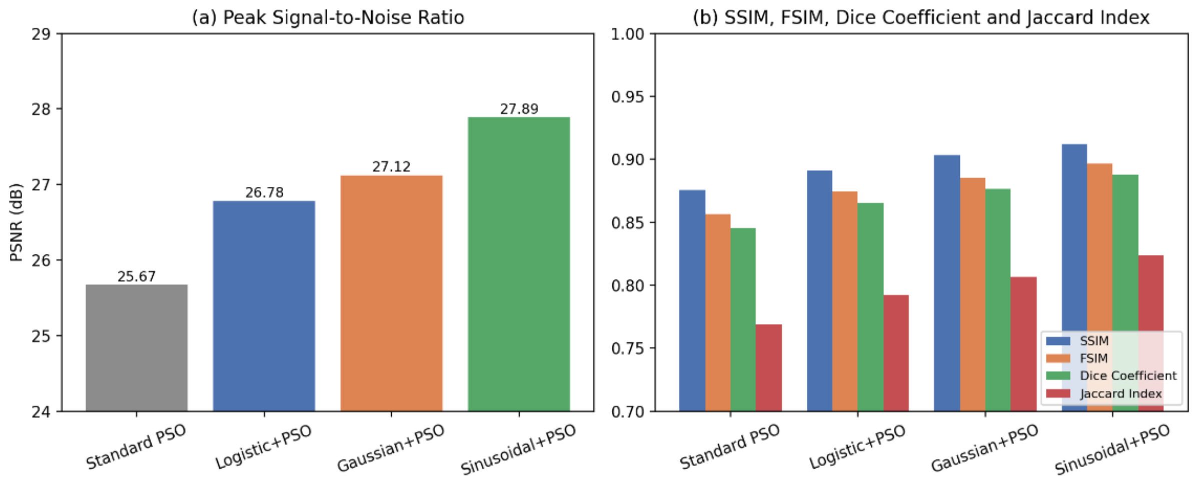

Figure 4.1: Performance metrics comparison across CE-PSO variants and Standard PSO

The three CE-PSO variants also differ in how quickly they reach their solutions. Sinusoidal+PSO exhibited the fastest convergence, reaching optimal fitness in an average of 41 iterations, representing a 29.3% improvement over Standard PSO (58 iterations), a 21.2% improvement over Logistic+PSO (52 iterations), and a 10.9% improvement over Gaussian+PSO (46 iterations). The convergence curves show that Sinusoidal+PSO maintains the best balance between exploration and exploitation, with the highest initial exploration rate in the first 20 iterations and the smoothest transition to the exploitation phase; it also shows the lowest fitness standard deviation across independent runs, indicating superior stability and consistency. All three CE-PSO algorithms demonstrated improvements over Standard PSO, with PSNR improvements ranging from 4.32% (Logistic+PSO) to 8.65% (Sinusoidal+PSO) and Dice Coefficient improvements from 2.34% to 4.97%, and all three variants demonstrated robust performance across image categories, including natural scenes, animals, buildings, textures, and objects.

4.1 Discussion of Findings

The superior performance of Sinusoidal+PSO can be attributed to several factors. First, the sinusoidal map provides smooth and continuous transitions between successive values, enabling gradual exploration of the search space without abrupt jumps that may overlook optimal threshold regions. Second, its U-shaped distribution concentrates values near the extremes of the search interval, which is advantageous for threshold selection because optimal thresholds frequently occur at intensity boundaries separating distinct image regions. Additionally, the dynamic sinusoidal parameter promotes adaptive search behaviour by gradually shifting the optimisation process from exploration to exploitation as the iterations progress, while the incorporated constriction coefficient ensures stable convergence while preserving population diversity, thereby reducing the likelihood of premature convergence to suboptimal solutions. These characteristics collectively contribute to the superior segmentation quality, stability, and optimisation performance achieved by the Sinusoidal+PSO algorithm.

When the three selected chaotic maps are compared on the basis of their influence on optimisation performance, convergence behaviour, and solution quality, chaotic maps with better diversity and exploration capability are found to improve PSO performance more consistently, with the sinusoidal chaotic map achieving superior convergence, stability, and optimisation accuracy compared with the other two maps. In answer to the research questions posed at the outset of this study, the smooth, U-shaped distribution of the Sinusoidal map proves highly effective for image segmentation because it concentrates chaotic values at intensity boundaries where optimal thresholds commonly reside, while providing gradual exploration of the search space; across the five evaluation metrics, Sinusoidal+PSO is recommended for high-accuracy applications requiring precise boundary delineation (27.89 dB PSNR, 0.8876 Dice Coefficient), Gaussian+PSO for problems requiring strong mixing and stagnation prevention, and Logistic+PSO as a computationally simple reference implementation for baseline comparison.

5.0 CONCLUSION

This study evaluated and compared three chaos-enhanced Particle Swarm Optimisation (CE-PSO) variants, Logistic+PSO, Sinusoidal+PSO, and Gaussian+PSO, for image segmentation by multilevel thresholding on the BSDS500 dataset, addressing the limitations of conventional PSO, particularly premature convergence and inadequate exploration of the search space, by integrating chaotic sequences into population initialisation, inertia-weight adaptation, acceleration-coefficient adjustment, and particle perturbation. The results demonstrate that integrating chaotic maps into PSO improves segmentation quality: all three CE-PSO variants outperformed Standard PSO across every evaluation metric, and Sinusoidal+PSO achieved the best overall performance, with a PSNR of 27.89 dB, SSIM of 0.9123, FSIM of 0.8967, Dice Coefficient of 0.8876, and Jaccard Index of 0.8234, followed by Gaussian+PSO and Logistic+PSO. Sinusoidal+PSO also converged fastest, reaching its solution in an average of 41 iterations, a 29.3% improvement over Standard PSO.

On the strength of these results, the study recommends the adoption of Sinusoidal+PSO for image-segmentation applications where maximum accuracy and improved optimisation performance are required, given its superior segmentation quality, convergence behaviour, and solution stability; Logistic+PSO is recommended as a suitable reference method for baseline comparison, given its effectiveness in evaluating the influence of chaotic enhancement on PSO performance; and Gaussian+PSO is recommended for optimisation problems that require strong mixing properties, since its chaotic behaviour provides increased diversity within the search process and supports exploration of complex solution spaces. This work provides a systematic comparison of three fundamentally different chaotic maps, the Logistic map with its parabolic distribution, the Sinusoidal map with its U-shaped distribution, and the Gaussian map with its highly skewed distribution, within the same PSO optimisation framework for image segmentation, establishing the superiority of the sinusoidal map for this application and demonstrating that the chaos-enhanced PSO framework provides a robust and reliable approach to multilevel-threshold image-segmentation tasks. Future work may extend this framework to additional chaotic maps, deep-learning integration, multi-objective optimisation, and colour or three-dimensional image segmentation.

References

1. Abualigah, L. (2025). Particle swarm optimization: Recent advances, applications, and future directions.

Artificial Intelligence Review.

2. Anjna, and Kaur, G. (2017). Image segmentation techniques: A review. International Journal of Computer Science and Mobile Computing, 6(6), 67–74.
3. Chen, L.-C., Papandreou, G., Schroff, F., and Adam, H. (2018). Encoder-decoder with atrous separable convolution for semantic image segmentation. In Proceedings of the European Conference on Computer Vision (ECCV) (pp. 801–818).
4. Dian, S., Ibrahim, Z., and colleagues. (2011). Particle swarm optimization: A survey of historical development and recent advances. International Journal of Computer Applications.
5. Elhoseny, M., Elminir, H. K., Riad, A. M., and Yuan, X. (2016). A hybrid model of Internet of Things and cloud computing to improve medical image segmentation. Journal of Computational Science, 17, 88–100.
6. Fister, I., Jr., Fister, D., Yang, X.-S., and Brest, J. (2015). A comprehensive review of chaos-based metaheuristics: Perspectives and challenges. Applied Mathematics and Computation, 252, 155–165.
7. Hu, J., Zhang, L., Wang, X., and colleagues. (2024). Multi-strategy particle swarm optimization for image segmentation. Expert Systems with Applications.
8. Huang, X., Liu, Y., Zhang, H., and colleagues. (2025). Chaos-enhanced particle swarm optimization for robust image segmentation. Engineering Applications of Artificial Intelligence.
9. Kapur, J. N., Sahoo, P. K., and Wong, A. K. C. (1985). A new method for gray-level picture thresholding using the entropy of the histogram. Computer Vision, Graphics, and Image Processing, 29(3), 273–285.
10. Limane, A., Zitouni, F., Harous, S., Aliane, H., and Talbi, H. (2025). Chaos-enhanced metaheuristics: Classification, comparison, and convergence analysis. Complex and Intelligent Systems, 11, Article 177. https://doi.org/10.1007/s40747-025-01791-2
11. Maja, S., Petrović, D., and colleagues. (2022). Chaotic initialization strategies for particle swarm optimization. Applied Soft Computing.
12. Minaee, S., Boykov, Y., Porikli, F., Plaza, A. J., Kehtarnavaz, N., and Terzopoulos, D. (2021). Image segmentation using deep learning: A survey. IEEE Transactions on Pattern Analysis and Machine Intelligence, 44(7), 3523–3542. https://doi.org/10.1109/TPAMI.2021.3059968
13. Mohamed, M. (2022). Particle swarm optimization-based K-means clustering for image segmentation. International Journal of Advanced Computer Science and Applications.
14. Mohsen, H., El-Dahshan, E.-S. A., El-Horbaty, E.-S. M., and Salem, A.-B. M. (2014). Improved particle swarm optimization for multilevel threshold image segmentation. Applied Soft Computing, 23, 588–597.
15. Okunlola, S. O., Baale, A. A., & Olabiyisi, S. O. (2026). Performance Evaluation of Selected Chaos-Enhanced Particle Swarm Optimisation for Image Segmentation. *Engineering and Technology Journal, 11*(7), 10904–10911. https://doi.org/10.47191/etj/v11i07.13
16. Olatunji, Babatunde Lekan, Olabiyisi, Stephen Olatunde, Oyeleye, Christopher Akinwale and Omotade, Adedotun Lawrence, 2025. "An Enhanced Chicken Swarm Optimization Algorithm Using Gaussian and Tent Chaotic Map Functions," International Journal of Research and Innovation in Applied Science, International Journal of Research and Innovation in Applied Science (IJRIAS), vol. 10(7), pages 653-664.
17. Otsu, N. (1979). A threshold selection method from gray-level histograms. IEEE Transactions on Systems, Man, and Cybernetics, 9(1), 62–66. https://doi.org/10.1109/TSMC.1979.4310076
18. Rosic, M., Sedak, M., Simic, M., and Pejovic, P. (2022). Chaos-Enhanced Adaptive Hybrid Butterfly Particle Swarm Optimization Algorithm for Passive Target Localization.
19. Sameh, A., Ben Abdallah, M., and colleagues. (2024). Comparative analysis of chaotic maps for optimization algorithms. Engineering Applications of Artificial Intelligence.
20. Wang, Z., Bovik, A. C., Sheikh, H. R., and Simoncelli, E. P. (2004). Image quality assessment: From error visibility to structural similarity. IEEE Transactions on Image Processing, 13(4), 600–612.
21. Ying, Y., Zhang, L., Chen, H., and colleagues. (2023). Image segmentation: Recent advances, challenges, and future directions. Information Fusion.
22. Youxiang, D., Chen, N., Chang, L., Ni, Y., and colleagues. (2022). CAPSO: Chaos adaptive particle swarm optimization algorithm. IEEE Access, 10, 28970–28989.
23. Yu, Y., Zhang, L., Chen, H., and colleagues. (2025). Comparative performance analysis of chaotic maps in metaheuristic optimization. Applied Soft Computing.