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Performance Evaluation of Particle Swarm Optimization Algorithm with Selected Chaos Maps for Image Segmentation

Oluwatoyin Florence Amusan[1], Stephen Olatunde Olabiyisi[2], Wasiu Oladimeji Ismaila[3] Isiaka & Akinkunmi Adeyemo[4]

Department of Computer Science, Ladoke Akintola University of Technology, Ogbomoso, Oyo State, Nigeria.

***Corresponding Author**: Oluwatoyin Florence Amusan[1], Stephen Olatunde Olabiyisi[2], Wasiu Oladimeji Ismaila[3] Isiaka & Akinkunmi Adeyemo[4]
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Abstract

Image segmentation is a fundamental operation in computer vision, and multilevel thresholding is among the techniques most commonly used to perform it; however, as the number of thresholds increases, locating the best set of threshold values becomes computationally demanding, and conventional methods, together with the Particle Swarm Optimisation (PSO) algorithm ordinarily used to address this difficulty, frequently suffer from premature convergence and inadequate exploration of the search space. This study addressed these limitations by incorporating chaotic maps into PSO to sustain population diversity, discourage premature convergence, and improve segmentation accuracy. The aim was to evaluate three chaos-enhanced PSO (CE-PSO) variants, namely Tent+PSO, Sinusoidal+PSO, and Circle+PSO, for image segmentation through multilevel thresholding on the Berkeley Segmentation Dataset (BSDS500). Chaotic sequences generated by the Tent, Sinusoidal, and Circle maps replaced the pseudo-random number generators conventionally used for population initialisation, inertia-weight adjustment, acceleration-coefficient modulation, and particle perturbation. Five hundred BSDS500 images were preprocessed, and the three variants were implemented in Python and evaluated over 30 independent runs per algorithm using Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), Feature Similarity Index (FSIM), segmentation accuracy, and F1-score. Tent+PSO achieved a PSNR of 26.34 ± 1.02 dB, an SSIM of 0.9056 ± 0.0212, and an F1-score of 0.9362 ± 0.0080; Sinusoidal+PSO achieved a PSNR of 26.89 ± 0.95 dB, an SSIM of 0.9123 ± 0.0198, and an F1-score of 0.9411 ± 0.0074; and Circle+PSO achieved a PSNR of 26.12 ± 1.05 dB, an SSIM of 0.9012 ± 0.0224, and an F1-score of 0.9311 ± 0.0083. Sinusoidal+PSO recorded the highest mean value on all the five evaluation metrics. The study establishes that, for multilevel-thresholding image segmentation on natural images of the kind represented in BSDS500, the Sinusoidal map is the most effective of the three chaotic maps evaluated, followed by the computationally inexpensive Tent map, with the two-parameter Circle map performing least effectively despite its additional tunability.

Keywords: *Image Segmentation, Multilevel Thresholding, Chaos-Enhanced Particle Swarm Optimisation, BSDS500.*

1.0 Introduction

Image segmentation is a fundamental preprocessing step in computer vision, involving the partitioning of a digital image into distinct regions to simplify its representation for further analysis; it underpins applications ranging from medical image analysis and object recognition to remote sensing and industrial inspection (Yuheng and Hao, 2017; Anjna and Kaur, 2017). Among the numerous segmentation approaches available, multilevel thresholding is widely favoured for its conceptual simplicity, computational efficiency, and ease of implementation, partitioning an image's histogram into multiple classes by selecting threshold values that optimise an objective function such as Otsu's between-class variance (Otsu, 1979) or Kapur's entropy (Kapur, Sahoo and Wong, 1985). While effective for bi-level segmentation, the search space for threshold combinations grows exponentially as the number of desired levels increases, rendering exhaustive search infeasible beyond a small number of thresholds and motivating the use of metaheuristic optimisation algorithms.

Particle Swarm Optimisation (PSO), a population-based stochastic technique inspired by the social behaviour of bird flocking and fish schooling, has been widely applied to multilevel thresholding because of its simplicity, few tunable parameters, and fast early-iteration convergence (Bai, 2010). However, standard PSO is known to suffer from premature convergence and loss of population diversity, particularly in later iterations, which reduces its ability to escape local optima; these weaknesses become more pronounced as the dimensionality of the thresholding problem increases. A growing body of research has explored chaos theory as a remedy: chaotic maps are deterministic, non-linear systems that exhibit pseudo-random, ergodic, non-repetitive behaviour while remaining bounded within a defined range, and substituting chaotic sequences for the pseudo-random number generators conventionally used in PSO, at population initialisation, inertia-weight adjustment, acceleration-coefficient modulation, and particle-velocity perturbation, has been shown to sustain higher population diversity and reduce the risk of premature convergence.

Numerous chaotic maps exist, each with distinct statistical and dynamical properties, and the choice of map can meaningfully affect optimisation performance. This study focuses on three such maps, the Tent map, the Sinusoidal map, and the Circle map, embedding each into a standard PSO framework and evaluating the resulting chaos-enhanced PSO (CE-PSO) variants on a multilevel-thresholding image-segmentation task using the Berkeley Segmentation Dataset (BSDS500). While chaos theory has been proposed as a mechanism for mitigating PSO's weaknesses, most existing studies examine a single chaotic map in isolation, or compare chaotic PSO variants using only a narrow set of metrics such as fitness value or PSNR alone, without a comprehensive, standardised comparison across multiple image-quality and segmentation-accuracy metrics on a large, diverse benchmark dataset; comparative studies involving the Tent, Sinusoidal, and Circle maps within the same PSO framework, under identical experimental conditions, remain scarce.

The aim of this research is therefore to evaluate the performance of the Tent, Sinusoidal, and Circle chaos maps in enhancing PSO for image segmentation. The specific objectives are to (i) integrate the selected chaos maps into the PSO algorithm to improve its exploration-exploitation balance; (ii) implement the resulting Tent+PSO, Sinusoidal+PSO, and Circle+PSO variants and apply them to image segmentation using Python; and (iii) compare their performance using PSNR, SSIM, FSIM, segmentation accuracy, and F1-score. In line with this aim, the study answers two research questions: (i) which of the selected chaotic maps provides the best segmentation quality; and (ii) how do the three CE-PSO variants compare with one another across the evaluated metrics.

2.0 Related Works

The closest methodological precedent for the present study is Arasomwan and Adewumi (2014), who experimentally compared nine chaotic maps, including Tent, Sinusoidal, and Circle, embedded within the inertia-weight component of two PSO variants, tested across five benchmark functions at varying dimensionalities. Their central finding, that no single chaotic map dominates across all problems and dimensions, with performance rankings shifting according to test function and dimensionality, directly informs the present study's interpretation of its own closely matched results; however, their study applies chaotic substitution only within the inertia-weight component and evaluates performance on mathematical benchmark functions rather than a real-world segmentation task, a gap the present study addresses by extending chaotic substitution across four PSO components and applying the comparison to multilevel-thresholding-based segmentation on natural images.

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 and Moronkeji *et al*. (2026) evaluated 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).

Duan et al. (2022) proposed CAPSO, combining nonlinear adaptive inertia weight and acceleration coefficients with Logistic-map chaotic initialisation and a chaotic local-search control factor, demonstrating superior convergence accuracy and stability over standard PSO and several chaos-enhanced comparators across the CEC2013 benchmark suite, and providing rigorous empirical evidence that chaotic initialisation yields better ergodicity than random initialisation. Rosić et al. (2022) embedded a logistic chaotic map into the PSO inertia-weight component alone, combined with an adaptive Butterfly Optimisation Algorithm, for a passive target-localisation problem, illustrating a narrower, single-map, single-component design in contrast to the present study's fuller four-substitution-point, three-map comparison. Limane et al.

(2025), in a comprehensive survey spanning 2013 to 2024, proposed a six-category taxonomy of chaos-metaheuristic integration points, finding that most tested chaotic variants outperformed a random-distribution baseline while explicitly flagging map selection, absent extensive trial-and-error, as an unresolved open problem in the field, a problem the present study addresses directly through controlled, problem-specific empirical testing of three candidate maps.

A separate cluster of studies characterises the intrinsic dynamical quality of individual chaotic maps using standardised tests. Htiti, Akharraz and Ahaitouf (2025) benchmarked a novel improved Sine map against Logistic, Sine, Tent, and Skew Tent maps using Lyapunov exponent, bifurcation diagram, 0-1 test, and sample-entropy analysis, demonstrating that the classical Tent map possesses a comparatively narrow chaotic parameter range. Soni, Thukral and Kanwar (2024) similarly quantified the Tent map's limitations for smart-grid cryptography, reporting only 85% chaotic-regime coverage and a Maximum Lyapunov Exponent of 0.6, against 99% coverage and 4.7 for newer hybrid maps, and Aouissaoui et al. (2022) reported comparable figures for the Tent map against several compound maps using a four-test battery. This literature is directly relevant to this study's treatment of the Tent map's known limitations, but none of these studies apply their characterised maps to PSO or to image segmentation.

A further cluster establishes precedent for the benchmarking methodology adopted in this study. Estrada and Jepson (2009) introduced a computationally efficient boundary-matching algorithm for precision-recall evaluation against human ground truth on BSDS, remaining the foundational reference for BSD-based precision-recall methodology, while Pantofaru and Hebert (2005) compared mean-shift, graph-based, and hybrid algorithms on BSDS using a normalised probabilistic index, establishing precedent for multi-algorithm, multi-metric BSD-based comparison. Udupa et al. (2006) proposed a rigorous multi-parameter segmentation evaluation framework distinguishing recognition from delineation accuracy, providing methodological grounding for the present study's use of multiple complementary metrics rather than a single score. Taken together, these studies confirm that chaos-enhanced PSO reliably outperforms its non-chaotic counterpart and that map selection remains an open, problem-dependent question, but most existing chaos-PSO studies examine either a single map in isolation or compare multiple maps only on synthetic benchmark functions rather than real image-segmentation tasks; no reviewed study combines a controlled, multi-map (Tent, Sinusoidal, Circle) CE-PSO comparison, applied across a comprehensive four-point chaotic-substitution design, evaluated using a full multi-metric protocol, on a large, standardised natural-image benchmark such as BSDS500. This precise combination constitutes the specific contribution of the present study.

3.0 Methodology

This section presents the methodology adopted for the comparative evaluation of three chaos-enhanced PSO (CE-PSO) variants, Tent+PSO, Sinusoidal+PSO, and Circle+PSO, on a multilevel-thresholding image-segmentation task, covering the research framework, dataset, chaotic-map integration, algorithmic design, implementation, and evaluation metrics.

3.1 Methodology Framework

The overall research methodology follows a systematic experimental design consisting of five sequential phases: data acquisition, image preprocessing, formulation of the CE-PSO algorithms, implementation in Python, and performance evaluation. Each phase 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.

3.2 Data Acquisition

The Berkeley Segmentation Dataset (BSDS500) is used as the benchmark for this study. It comprises 500 natural images (321 × 481 or 481 × 321 pixels) with 5–7 human-annotated ground-truth segmentations per image, spanning natural scenes, animals, buildings, textures, and objects. To ensure a systematic and unbiased evaluation, the dataset is partitioned into training (200 images, algorithm optimisation), validation (100 images, parameter tuning), and testing (200 images, final evaluation) subsets, as summarised in Table 1.

Table 1: BSDS500 Dataset Distribution

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

3.3 Image Preprocessing

Each RGB image is converted to 8-bit grayscale using the luminance-weighted transformation:

$$I(x,y) = 0.299 \cdot R(x,y) + 0.587 \cdot G(x,y) + 0.114 \cdot B(x,y) \quad (1)$$

and rescaled to fully span the [0, 255] range using min-max normalisation:

$$I_{norm}(x,y) = [(I(x,y) - I_{min}) / (I_{max} - I_{min})] \times 255 \quad (2)$$

For each image, the human-annotated boundaries supplied with the dataset are consolidated by majority vote into a single region-label map used as the ground-truth reference during evaluation.

3.4 Formulation of the CE-PSO Algorithms

Each CE-PSO variant follows an identical procedural structure, differing only in which chaotic map generates the sequence substituted at four points: population initialisation, inertia-weight adjustment, acceleration-coefficient modulation, and particle perturbation. Given the next iterate CM(·) of the selected map, particle positions are seeded as $x_i(0) = x_{min} + CM(x_0) \cdot (x_{max} - x_{min})$; the inertia weight is updated each iteration as $w(t) = w_{min} + (w_{max} - w_{min}) \cdot CM(x_t)$; the acceleration coefficients are updated as $c_1(t), c_2(t) = c_{min} + (c_{max} - c_{min}) \cdot CM(x_t), CM(x_t')$; and a bounded perturbation $x_i(t) = x_i(t) + \delta \cdot CM(x_t) \cdot (x_{max} - x_{min})$ is applied at fixed intervals to counteract incipient premature convergence.

3.4.1 Tent+PSO Algorithm

Tent+PSO embeds the piecewise-linear Tent map, $x_{n+1} = 2x_n$ for $x_n < 0.5$ and $x_{n+1} = 2(1 - x_n)$ for $x_n \geq 0.5$ (symmetric parameter $a = 0.5$), at each of the four substitution points. Its uniform invariant density gives the swarm broad, evenly spread coverage of the search space at minimal computational overhead. The procedure is given in Algorithm 1.

Algorithm 1: Tent Map-Enhanced PSO (Tent+PSO)

Input: N=30, Tmax=100, D=thresholds, a=0.5, x0=0.1,
[wmin,wmax]=[0.4,0.9], $c_1=c_2=2.0$, image I
Output: Gbest thresholds, best fitness, segmented image
1. Seed chaotic sequence x0; generate CMTent(·) sequence
2. Initialise N particles: xi(0)=xmin+CMTent(x0)(xmax−xmin)
3. Evaluate f(xi) via Otsu/Kapur objective; set pbesti=xi, gbest=best
4. For t = 1 to Tmax:
   For each particle i:
      w(t)=wmin+(wmax−wmin)·CMTent(xt)
      c1(t),c2(t) modulated via CMTent(xt), CMTent(xt′)
      vi(t+1)=w(t)vi(t)+c1(t)CMTent(xt)(pbesti−xi)
            +c2(t)CMTent(xt′)(gbest−xi)
      xi(t+1)=xi(t)+vi(t+1)
      If t mod 10==0: xi(t+1)+=δ·CMTent(xt)(xmax−xmin)
      Evaluate f(xi); update pbesti, gbest
5. Return gbest as optimal threshold set

3.4.2 Sinusoidal+PSO Algorithm

Sinusoidal+PSO follows an identical procedural structure, substituting the smooth, trigonometric Sinusoidal map, $x_{n+1} = a \cdot x_n^2 \cdot \sin(\pi x_n)$ with $a \approx 2.3$, at the same four points. Its continuous, non-uniform trajectory produces a more gradual exploration pattern than the Tent map's sharper, angular trajectory. The procedure is given in Algorithm 2.

Algorithm 2: Sinusoidal Map-Enhanced PSO (Sinusoidal-PSO)

Input: N=30, Tmax=100, D=thresholds, a≈2.3, x0=0.1,
[wmin,wmax]=[0.4,0.9], $c_1=c_2=2.0$, image I
Output: Gbest thresholds, best fitness, segmented image
1. Seed chaotic sequence x0; generate CMSin(·) sequence

```
2. Initialise N particles: xi(0)=xmin+CMSin(x0)(xmax−xmin)
3. Evaluate f(xi) via Otsu/Kapur objective; set pbesti=xi, gbest=best
4. For t = 1 to Tmax:
   For each particle i:
     w(t)=wmin+(wmax−wmin)·CMSin(xt)
     c1(t),c2(t) modulated via CMSin(xt), CMSin(xt′)
     vi(t+1)=w(t)vi(t)+c1(t)CMSin(xt)(pbesti−xi)
              +c2(t)CMSin(xt′)(gbest−xi)
     xi(t+1)=xi(t)+vi(t+1)
     If t mod 10==0: xi(t+1)+=δ·CMSin(xt)(xmax−xmin)
     Evaluate f(xi); update pbesti, gbest
5. Return gbest as optimal threshold set
```

3.4.3 Circle+PSO Algorithm

Circle+PSO substitutes the two-parameter, rotation-based Circle map, $x_{n+1} = \mathrm{mod}(x_n + b - (a/2\pi)\cdot\sin(2\pi x_n), 1)$ with $a = 0.5$ and $b = 0.2$, at the same four points. Its modulo-bounded, phase-driven dynamics give it a structurally distinct exploration pattern, offering an additional degree of tunability at the cost of marginally higher computational complexity. The procedure is given in Algorithm 3.

Algorithm 3: Circle Map-Enhanced PSO (Circle-PSO)

```
Input: N=30, Tmax=100, D=thresholds, a=0.5, b=0.2, x0=0.1,
[wmin,wmax]=[0.35,0.92], c1=c2=1.7, image I
Output: Gbest thresholds, best fitness, segmented image
1. Seed chaotic sequence x0; generate CMCircle(·) sequence
2. Initialise N particles: xi(0)=xmin+CMCircle(x0)(xmax−xmin)
3. Evaluate f(xi) via Otsu/Kapur objective; set pbesti=xi, gbest=best
4. For t = 1 to Tmax:
   For each particle i:
     w(t)=wmin+(wmax−wmin)·CMCircle(xt)
     c1(t),c2(t) modulated via CMCircle(xt), CMCircle(xt′)
     vi(t+1)=w(t)vi(t)+c1(t)CMCircle(xt)(pbesti−xi)
              +c2(t)CMCircle(xt′)(gbest−xi)
     xi(t+1)=xi(t)+vi(t+1)
     If t mod 10==0: xi(t+1)+=δ·CMCircle(xt)(xmax−xmin)
     Evaluate f(xi); update pbesti, gbest
5. Return gbest as optimal threshold set
```

3.5 Implementation and Experimental Environment

The three CE-PSO variants were implemented in Python, using NumPy for numerical computation, OpenCV and scikit-image for image processing and segmentation, and Matplotlib for visualisation. Table 2 summarises the hardware and software environment, and Table 3 summarises the common parameter configuration adopted across all three variants to ensure a fair comparison.

Table 2: Experimental Environment

Component	Specification
Processor	Intel Core i7-10750H @ 2.60GHz (6 cores, 12 threads)
RAM	16 GB DDR4 @ 2666 MHz
Storage	512 GB NVMe SSD
Operating System	Windows 11 Pro / Ubuntu 22.04 LTS
Programming Language	Python 3.9+
Key Libraries	NumPy, scikit-image, OpenCV, Matplotlib, Pandas, SciPy

Table 3: CE-PSO Parameter Settings

Parameter	Tent+PSO	Sinusoidal+PSO	Circle+PSO
Swarm size (N)	30	30	30
Max. iterations	100	100	100
Inertia weight [wmin,wmax]	[0.4, 0.9]	[0.4, 0.9]	[0.35, 0.92]
Acceleration coeff. (c1,c2)	2.0, 2.0	2.0, 2.0	1.7, 1.7
Perturbation scaling (δ)	0.05	0.05	0.05
Perturbation interval	Every 10 iter.	Every 10 iter.	Every 10 iter.
Independent runs	30	30	30
Objective function	Otsu / Kapur	Otsu / Kapur	Otsu / Kapur
Map control parameter(s)	a = 0.5	a ≈ 2.3	a=0.5, b=0.2

3.6 Evaluation Metrics

PSNR, SSIM, and FSIM measure image-quality preservation, structural similarity, and feature consistency between the segmented and reference grayscale image, while segmentation accuracy, precision, recall, and F1-score measure pixel-level agreement with the consolidated ground truth:

$$PSNR = 10\cdot log10(MAXI2 / MSE),\ MAXI = 255 \quad (3)$$

$$SSIM(x,y) = [(2\mu x\mu y+C1)(2\sigma xy+C2)] / [(\mu x2+\mu y2+C1)(\sigma x2+\sigma y2+C2)] \quad (4)$$

$$FSIM = \Sigma[PCm(x)\cdot GMm(x)] / \Sigma\ PCm(x) \quad (5)$$

$$Accuracy = (TP+TN) / (TP+TN+FP+FN) \quad (6)$$

$$F1\text{-}Score = 2\cdot(Precision\cdot Recall) / (Precision+Recall) \quad (7)$$

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 performance difference can be attributed to the chaotic map employed rather than to inconsistencies in experimental treatment.

4.0 Results and Discussion

This section reports the segmentation quality achieved by each of the three CE-PSO variants across the five evaluation metrics, over 30 independent runs per algorithm on the BSDS500 test images, following the experimental configuration summarised above (4 thresholds, 30 particles, 100 iterations).

Table 4: Segmentation Quality Metrics Comparison (Mean ± SD over 30 Runs)

Algorithm	PSNR (dB)	SSIM	FSIM	F1-Score
Tent+PSO	26.34 ± 1.02	0.9056 ± 0.0212	0.8923 ± 0.0234	0.9362 ± 0.0080
Sinusoidal+PSO	**26.89 ± 0.95**	**0.9123 ± 0.0198**	**0.8989 ± 0.0212**	**0.9411 ± 0.0074**
Circle+PSO	26.12 ± 1.05	0.9012 ± 0.0224	0.8878 ± 0.0245	0.9311 ± 0.0083

Sinusoidal+PSO records the highest mean value on all five metrics shown, and on all seven metrics evaluated overall (including accuracy = 0.9645, precision = 0.9467, recall = 0.9356), followed by Tent+PSO, with Circle+PSO recording the lowest mean value on every metric. Sinusoidal+PSO also records the lowest standard deviation on six of the seven metrics, indicating that it is not only the best-performing but also the most consistent of the three variants across independent runs. It achieves the highest PSNR (26.89 dB), outperforming Tent+PSO by 0.55 dB (+2.09%) and Circle+PSO by 0.77 dB (+2.95%), and the highest F1-score (0.9411), a 0.52% improvement over Tent+PSO and a 1.07% improvement over Circle+PSO, with the closest balance between precision (0.9467) and recall (0.9356) among the three variants.

Table 5: Relative Performance Improvement

Comparison	PSNR	SSIM	F1-Score	Sig.
Sinusoidal vs Tent	+2.09%	+0.74%	+0.52%	$p < 0.05$
Sinusoidal vs Circle	+2.95%	+1.23%	+1.07%	$p < 0.01$
Tent vs Circle	+0.84%	+0.49%	+0.55%	$p < 0.05$

The improvement margin is largest on PSNR (0.84% to 2.95%) and smallest on SSIM, FSIM, and F1-score (0.49% to 1.25%), indicating that chaotic-map choice has a more pronounced effect on raw signal fidelity than on structural- and classification-oriented metrics. All three pairwise comparisons, obtained using the Wilcoxon signed-rank test, are statistically significant at the 0.05 level, with the Sinusoidal-versus-Circle comparison significant at the more stringent 0.01 level, indicating that Sinusoidal+PSO's advantage over Circle+PSO is the most robust of the three pairwise differences observed.

4.1 Discussion of Findings

Sinusoidal+PSO's advantage across all seven evaluation metrics can plausibly be attributed to the specific dynamical properties of the Sinusoidal map. Unlike the piecewise-linear Tent map, whose trajectory changes direction sharply at its breakpoint, the Sinusoidal map is smooth and continuously differentiable, producing a more gradual pattern of perturbation when substituted into the inertia weight, acceleration coefficients, and velocity terms of PSO; this smoother trajectory appears to translate into more consistent step sizes in the swarm's search behaviour, reflected in Sinusoidal+PSO's lowest standard deviation on six of the seven metrics. This interpretation is further supported by its precision-recall balance, suggesting that its advantage stems from a genuinely more balanced improvement in both boundary preservation and region homogeneity rather than from favouring one type of segmentation error over another.

Sinusoidal+PSO's narrow but statistically significant margin over Tent+PSO (0.52% to 2.09% across metrics) is consistent with, rather than contrary to, the finding of Arasomwan and Adewumi (2014) that the Sinusoidal and Tent maps are closely matched in PSO-embedding performance, with neither map achieving decisive dominance over the other across benchmark functions; the present results extend this finding from synthetic benchmark-function optimisation to a real image-segmentation task. Circle+PSO, built on the two-parameter, rotation-based Circle map, consistently records the lowest performance among the three variants, indicating that the additional tunability afforded by its two control parameters ($a = 0.5$, $b = 0.2$) does not, in this application, translate into an advantage over the single-parameter Tent and Sinusoidal maps, consistent with the literature's general finding that the Circle map's performance is problem- and dimension-dependent rather than uniformly competitive (Arasomwan and Adewumi, 2014).

In answer to the research questions posed in Section 1.0: Sinusoidal+PSO provides the best segmentation quality of the three variants evaluated, recording the highest mean value on all seven metrics and the lowest standard deviation on six of the seven; and the ranking Sinusoidal+PSO > Tent+PSO > Circle+PSO holds consistently across all seven metrics, with the margin widest on PSNR (up to 2.95%) and narrowest on SSIM, FSIM, and F1-score (0.49% to 1.25%), and all three pairwise differences statistically significant.

5.0 Conclusion and Recommendations

This study addressed the premature convergence and loss of population diversity that limit standard PSO in multilevel-thresholding image segmentation by incorporating chaotic maps into the PSO framework. Three CE-PSO variants, Tent+PSO, Sinusoidal+PSO, and Circle+PSO, were implemented in Python and evaluated under identical conditions on the BSDS500 dataset over 30 independent runs per algorithm. Sinusoidal+PSO achieved the highest mean value on all seven metrics evaluated (PSNR = 26.89 dB, SSIM = 0.9123, FSIM = 0.8989, accuracy = 0.9645, precision = 0.9467, recall = 0.9356, F1-score = 0.9411), followed by Tent+PSO, with Circle+PSO recording the lowest mean value on every metric; all three pairwise differences were confirmed statistically significant using the Wilcoxon signed-rank test ($p < 0.05$, and $p < 0.01$ for the Sinusoidal-versus-Circle comparison).

Sinusoidal+PSO is recommended as the preferred CE-PSO variant for multilevel-thresholding image segmentation tasks similar in scope to this study, given its consistent and statistically significant advantage across all seven evaluated metrics. Where a simpler, single-parameter chaotic map is preferred for ease of implementation, Tent+PSO is a reasonable alternative, since it significantly outperforms Circle+PSO despite its lower computational and mathematical complexity; Circle+PSO's two control parameters did not yield a performance advantage in this study, so researchers considering the Circle map for similar tasks should not assume that its additional tunability will translate into better segmentation quality without problem-specific testing. Because this study compared the three CE-PSO variants only against one another, future work should include a standard, non-chaotic PSO baseline under the same experimental conditions to quantify the overall benefit of chaos enhancement itself. Finally, given the literature's finding that chaotic-map performance is problem-dependent rather than universal, researchers should regard the Sinusoidal map's advantage as specific to this multilevel-thresholding image-segmentation task on BSDS500, and should re-evaluate map choice empirically for substantially different tasks or datasets.

This study contributes a controlled, multi-map comparison of the Tent, Sinusoidal, and Circle chaotic maps, embedded identically across four substitution points of the PSO algorithm and evaluated on a real multilevel-thresholding image-segmentation task rather than on synthetic benchmark functions alone, establishing a statistically validated performance ranking (Sinusoidal+PSO > Tent+PSO > Circle+PSO) across seven complementary segmentation-quality metrics on the BSDS500 benchmark, and extending the finding of Arasomwan and Adewumi (2014) that the Tent and Sinusoidal maps are closely matched in PSO-embedding performance from synthetic benchmark-function optimisation to a real image-segmentation application.

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