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PSO-SAM: Segmentation of Aerial Images using Particle Swarm Optimization and Segment Anything Model in Urban Environments

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ABSTRACT

Accurate segmentation of orthoimages remains a significant challenge in remote sensing, particularly within complex urban environments and low-quality datasets. This study introduces PSO-SAM, a novel hybrid framework that enhances the Segment Anything Model (SAM) by automatically tuning key input parameters—namely points_per_side and pred_iou_thresh—using Particle Swarm Optimization (PSO). Evaluated on a 2013 low-resolution orthoimages of Yazd, Iran, PSO-SAM demonstrates substantial improvements over the baseline SAM in all major segmentation metrics: IoU (0.1882, +65.5%), Precision (0.2705, +17.8%), Dice Coefficient (0.3168, +55.2%), Recall (0.3821, +108%), and F1-Score (0.3168, +55.2%). Although the achieved absolute segmentation metrics remain modest due to the challenging characteristics of the dataset and zero-shot limitations of SAM, the proposed optimization framework consistently improves segmentation quality across all evaluation criteria, and absolute metrics are reported to provide balanced interpretation. The sharp rise in Recall highlights PSO-SAM's capacity to reduce false negatives and detect geographic features more comprehensively. To the best of our knowledge, limited studies have explored the integration of SAM with metaheuristic optimization strategies for urban aerial image segmentation. While absolute metric values remain lower than state-of-the-art benchmarks—primarily due to data limitations and the sensitivity of PSO—the results emphasize the potential of PSO-SAM for automated segmentation in constrained remote sensing scenarios. Future directions include improving data quality, exploring advanced optimization strategies, and leveraging higher-resolution or multispectral datasets to close the performance gap.

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1. Introduction

Segmentation of aerial images is a critical task in various remote sensing applications, including urban planning, environmental monitoring, and disaster response. This process involves partitioning imagery into semantically meaningful regions to extract and analyse geographic features. While traditional segmentation techniques—such as thresholding and edge detection—have been widely used, they are increasingly being supplanted by deep learning-based models due to their superior accuracy and flexibility in complex visual scenes.

Among the recent advancements in this field is the Segment Anything Model (SAM), introduced by Meta AI in 2023 (Kirillov et al., 2023). SAM is a powerful zero-shot segmentation model trained on the SA-1B dataset, which includes over one billion segmentation masks and 11 million images. As a foundation model, SAM supports both instance and semantic segmentation across diverse domains using intuitive prompts such as points, boxes, or text. Leveraging a Vision Transformer and an interactive decoder, SAM has demonstrated strong generalization capabilities across medical imaging, satellite imagery, and agricultural mapping (Carraro, Sozzi, & Marinello, 2023; Deng et al., 2025; Osco et al., 2023). We selected SAM as the base model due to its recent emergence as a general-purpose segmentation framework and its demonstrated versatility across domains, making it a compelling candidate for remote sensing adaptation.

Despite these strengths, SAM's default parameter configurations may be suboptimal in specialized scenarios, such as segmenting low-resolution orthoimages or densely structured urban areas. To address this limitation, we propose using Particle Swarm Optimization (PSO)—a metaheuristic algorithm introduced by (Kennedy & Eberhart, 1995)—to automatically tune SAM's critical input parameters, including points_per_side and pred_iou_thresh. PSO is particularly suited for navigating complex parameter spaces and has been successfully applied in various computer vision tasks.

In this paper, we introduce PSO-SAM, a hybrid segmentation framework that combines the robustness of SAM with the adaptive tuning capabilities of PSO. We evaluate the method on a challenging 2013 ortho-image of Yazd, Iran, characterized by low spatial resolution and complex urban structures. Through a comparative analysis with the baseline SAM model, we aim to assess the impact of automated parameter optimization on segmentation accuracy in constrained remote sensing contexts. This is among the first studies to integrate SAM with an optimization strategy specifically, highlighting a novel contribution to remote sensing segmentation.

2. Related Work

Image segmentation is a central problem in both computer vision and remote sensing, where accurate delineation of objects is essential for downstream tasks such as classification, change detection, and feature extraction. Traditional segmentation approaches—including region-based, clustering-based, and edge-based methods—often struggle in complex or noisy imagery, particularly in heterogeneous urban scenes (Gonzalez, 2009; Pal & Pal, 1993; Sonka, Hlavac, & Boyle, 2013).

Recent advances in deep learning have significantly improved segmentation performance. Models such as U-Net (Ronneberger, Fischer, & Brox, 2015) and Mask R-CNN (He, Gkioxari, Dollár, & Girshick, 2017) leverage convolutional architectures to learn spatial hierarchies of features, enabling precise semantic segmentation. However, these methods typically require task-specific training on large, annotated datasets, which may not be feasible for remote sensing imagery due to annotation costs and data variability. Moreover, their reliance on supervised learning limits adaptability across domains, whereas SAM offers a zero-shot alternative with broader generalization (Kirillov et al., 2023).

The Segment Anything Model (SAM), proposed by (Kirillov et al., 2023), represents a paradigm shift by enabling zero-shot segmentation across diverse domains without the need for retraining. SAM's vision-transformer-based architecture, trained on the large-scale SA-1B dataset, allows it to generate segmentation masks from simple prompts (e.g., points or boxes), making it broadly applicable across disciplines—from medical imaging to satellite-based monitoring (Carraro et al., 2023; Deng et al., 2025; Osco et al., 2023).

Nonetheless, several studies have reported a performance drop in applying SAM to specialized domains such as remote sensing, where image quality, object complexity, and domain-specific semantics limit generalization (Osco et al., 2023). To mitigate such challenges, optimization techniques have been introduced to tune the behaviour of segmentation models for domain-specific tasks.

Among these techniques, Particle Swarm Optimization (PSO) has emerged as a promising solution. Inspired by swarm intelligence, PSO has been employed to optimize hyperparameters in various deep learning frameworks, resulting in improved segmentation accuracy across multiple domains including microscopy, biomedical imaging, and satellite data (Archit et al., 2025; Zhang, Wang, Liu, & Xiong, 2025). Other optimization methods such as Genetic Algorithms (Goldberg, 1989), Differential Evolution (Storn & Price, 1997), and Bayesian Optimization (Snoek, Larochelle, & Adams, 2012) have also been explored in segmentation tasks. While each has its strengths, PSO offers a balance between simplicity, convergence speed, and adaptability, making it well-suited for tuning segmentation models in constrained environments. However, the integration of PSO with SAM—particularly for urban aerial imagery—has received limited attention in the literature.

This study addresses this gap by evaluating the effectiveness of a PSO-SAM framework, specifically designed for the segmentation of urban orthoimages. Our work contributes to the growing body of research aimed at improving general-purpose segmentation models for use in specialized and data-constrained remote sensing contexts.

3. Study Area

For this study, we utilized an ortho-image dataset of Yazd city, located in central Iran, captured in 2013 with a ground resolution of 0.15 meters (Figure 1). The image covers a densely built urban landscape characterized by a mix of residential, commercial, and infrastructural features, as well as scattered patches of vegetation.

Figure 1. Aerial ortho-image of the study area.

Yazd lies within an arid desert climate zone, which significantly influences the city's spatial structure. Urban development dominates the region, while vegetation is sparse and primarily confined to irrigated areas or ornamental greenery. These environmental and structural conditions pose challenges for automated image segmentation, as the visual contrast between built-up areas and natural elements is often minimal. Furthermore, object boundaries tend to be ambiguous due to the relatively low resolution of the imagery and the intricate texture of the urban fabric.

These characteristics make the Yazd dataset a suitable benchmark for evaluating the robustness of segmentation models in data-constrained and visually complex urban environments.

4. Segmentation Methods

In this study, we adopted the Segment Anything Model (SAM) for the segmentation of aerial orthoimages and proposed a novel enhancement strategy through Particle Swarm Optimization (PSO). The resulting hybrid framework, referred to as PSO-SAM, aims to improve SAM's segmentation accuracy by automatically optimizing its key input parameters.

Two core parameters were selected for optimization:

- **points_per_side**: Determines the density of input sampling points used for automatic mask generation. Increasing this value can improve the segmentation of smaller or irregularly shaped objects but incurs higher computational costs.
- **pred_iou_thresh**: Specifies the confidence threshold for accepting predicted masks based on Intersection over Union (IoU). A higher threshold promotes precision by filtering out low-confidence masks, but may reduce coverage in complex or cluttered scenes.

The proposed PSO-SAM framework is entirely training-free and operates only during the inference stage without modifying or fine-tuning the internal weights of SAM. PSO was employed to explore the parameter space efficiently and identify optimal configurations tailored to the characteristics of low-resolution urban imagery. As a population-based metaheuristic inspired by swarm intelligence, PSO has proven effective in navigating high-dimensional search spaces, particularly where gradient-based methods are impractical (Kennedy & Eberhart, 1995). In preliminary experiments, we evaluated the sensitivity of several SAM parameters on segmentation performance. Among them, points_per_side and pred_iou_thresh consistently showed the highest impact on recall and overall mask quality in urban aerial imagery. Other parameters, such as stability_score_thresh, exhibited minimal influence or led to unstable behavior during optimization. Therefore, we prioritized these two parameters for PSO-based tuning to maximize performance while maintaining computational efficiency. Compared to other optimization techniques such as Genetic Algorithms, Differential Evolution, or Bayesian Optimization, PSO offers a favorable balance between simplicity, convergence speed, and adaptability, making it suitable for this application.

We compared the performance of the following two segmentation configurations:

1. **Segment Anything Model (SAM):** SAM is a state-of-the-art zero-shot segmentation model that employs a Vision Transformer to extract image features and generate masks based on user-defined prompts or automated inputs. In this study, SAM was used in its automatic mask generation mode, which creates segmentation masks without manual intervention.
2. **PSO-SAM (Proposed Method):** The PSO-SAM framework dynamically adjusts SAM's input parameters via PSO, with the objective of maximizing segmentation performance. This integration is particularly

beneficial in challenging scenarios, such as urban remote sensing, where standard parameter values may be suboptimal.

The PSO algorithm was initialized with a range of plausible parameter values and iteratively updated to converge toward a configuration that yields improved segmentation metrics. Notably, the sharp improvement in Recall reflects PSO-SAM's ability to recover missed objects in cluttered scenes, although this gain stems from a relatively low baseline and is contextualized by reporting absolute metric values.

$$F1=\frac{2\times Precision\times Recall}{Precision+Recall}$$

The PSO optimization process aimed to maximize the F1-score as the objective function due to its balanced sensitivity to both false positives and false negatives. To ensure reproducibility, we summarize the key PSO hyperparameters used in our experiments: Population size (20), Number of iterations (30) and Inertia weight (0.7). These values were selected based on prior literature and empirical tuning to balance convergence speed and solution quality. A larger population or iteration count did not yield significant improvements in our case but increased computational cost. The resulting PSO-SAM approach enhances both precision and recall by balancing mask quality and spatial coverage.

5. Results and Discussion

To assess the performance of the baseline Segment Anything Model (SAM) and the proposed PSO-SAM framework, we employed five standard evaluation metrics widely used in image segmentation:

- Intersection over Union (IoU): Quantifies the overlap between predicted and ground truth masks as the ratio of their intersection to their union.
- Precision: Measures the proportion of true positives among all predicted foreground pixels.
- Recall: Indicates the percentage of actual foreground pixels that are correctly detected.
- Dice Coefficient: A similarity index that balances both false positives and false negatives to assess overall mask agreement.
- F1-Score: The harmonic mean of Precision and Recall, offering a composite indicator of segmentation accuracy.

These metrics provide a comprehensive evaluation of segmentation performance across various aspects of accuracy and completeness—critical for urban remote sensing applications.

The performance evaluation was conducted on a 2013 ortho-image of Yazd city using ground truth masks manually annotated by domain experts (Figure 2). These masks included pixel-level delineation of urban buildings. Given the image's relatively low resolution and dense urban layout, matching predicted masks with the ground truth posed considerable challenges. This complexity contributed to low baseline metric values, particularly Recall, which amplifies the relative percentage improvements observed in PSO-SAM. Furthermore, the presence of Orthorectification artifacts and limited spectral detail in the dataset constrained the absolute segmentation performance, despite optimization.

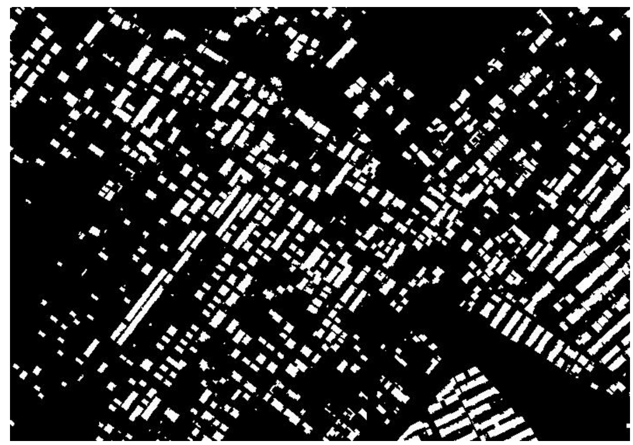


Figure 2. The ground truth image.

Table 1 summarizes the segmentation results for both models:

Table 1. Segmentation performance comparison between SAM and PSO-SAM.

Metric	SAM	PSO-SAM	Improvement (%)
IoU	11.37%	18.82%	+65.5%
Precision	22.96%	27.05%	+17.8%
Dice Coefficient	20.41%	31.68%	+55.2%
Recall	18.37%	38.21%	+108%
F1-Score	20.41%	31.68%	+55.2%

Figure 3 shows the comparison of segmentation performance between SAM and PSO-SAM across five evaluation metrics: IoU, Precision, Dice Coefficient, Recall, and F1-Score. PSO-SAM consistently outperforms SAM, demonstrating superior accuracy and robustness in all measured categories.

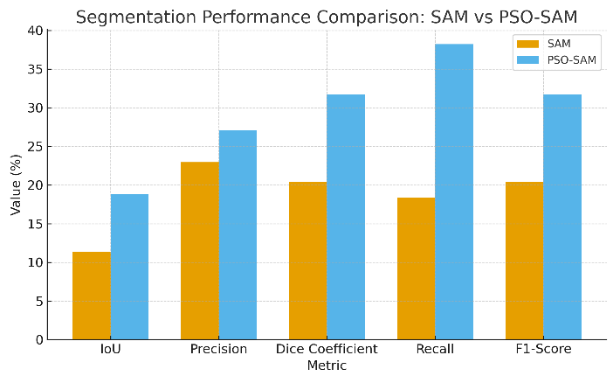
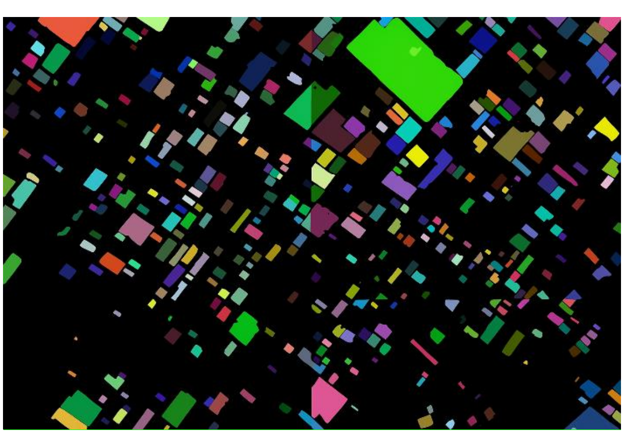


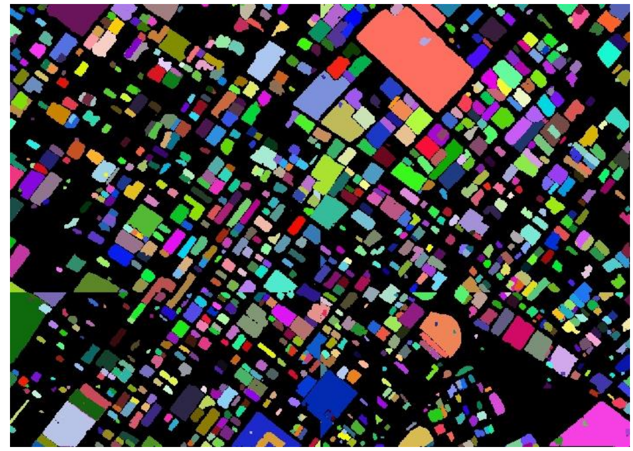
Figure 3. Comparison of segmentation performance between SAM and PSO-SAM.

The results demonstrate that PSO-SAM consistently outperforms the baseline SAM across all evaluation criteria. While the 108% increase in Recall is substantial, it stems from a relatively low baseline value (18.37%), and absolute metrics are reported to ensure balanced interpretation. This improvement indicates that the optimized model is more effective in identifying true foreground regions—reducing false negatives and capturing finer structural details in the urban fabric.

Visual comparisons between SAM and PSO-SAM outputs further highlight the qualitative improvements. As shown in Figure 4, the PSO-SAM model produces cleaner and more coherent segmentation masks with sharper object boundaries, particularly in densely built-up areas. Notably, PSO-SAM better preserves small building footprints and reduces fragmentation in cluttered zones, which are often missed by the baseline SAM. However, it is important to note that the relatively low resolution of the input image and the manual nature of ground truth annotations may limit the absolute performance ceiling and introduce annotation bias.



a



b

Figure 4. Qualitative comparison of segmentation outputs generated by (a) SAM and (b) PSO-SAM.

Despite these improvements, absolute performance values such as IoU = 0.1882 and Dice = 0.3168—remain below the levels commonly reported in remote sensing literature, where IoU and Dice values often range from 0.85 to 0.90 and 0.88 to 0.92, respectively. This gap underscores the challenges of applying segmentation models to low-quality urban imagery, where even optimized frameworks face structural and radiometric constraints. This discrepancy is likely attributed to several factors:

1. **Data limitations**: The 2013 ortho-image is relatively low in resolution (15 cm GSD) and exhibits significant radiometric noise.
2. **Ground truth inaccuracies**: Analysis revealed misalignments between the ortho-image and annotated masks. As illustrated in **Figure 5**, such discrepancies stem from:
   - Incomplete Orthorectification , leading to leaning effects in high-rise buildings (4a),
   - Presence of architectural overhangs or cantilevers not visible from nadir views (4b),
   - Inclusion of under-construction buildings in the labeled building class (4c).

These factors collectively reduce the achievable segmentation accuracy and explain the relatively low absolute metric values, despite the substantial relative improvements introduced by PSO-SAM. Future work will focus on validating the framework using higher-resolution or multispectral datasets with more rigorous ground truth annotations to further improve performance and generalizability.

3. **PSO sensitivity**: The optimization process is susceptible to local minima depending on initialization and population diversity.

These factors highlight the difficulty of segmentation in real-world, visually complex urban environments and emphasize the importance of high-quality input data and ground truth labels. Such limitations directly impact the achievable segmentation accuracy, explaining the relatively low absolute metric values despite notable relative improvements.

Nonetheless, the results underscore the potential of the PSO-SAM framework in enhancing segmentation performance in data-constrained scenarios. As one of the first studies to integrate PSO with SAM for urban aerial imagery, this work demonstrates a novel and adaptive approach to improving segmentation under challenging conditions. The automatic parameter tuning provided by PSO allows SAM to adapt better to task-specific conditions, improving reliability in identifying urban features.

Direct comparison with supervised deep learning models such as U-Net or DeepLab is challenging because those frameworks generally rely on extensive task-specific training datasets, whereas SAM operates in a zero-shot setting without domain-specific retraining.

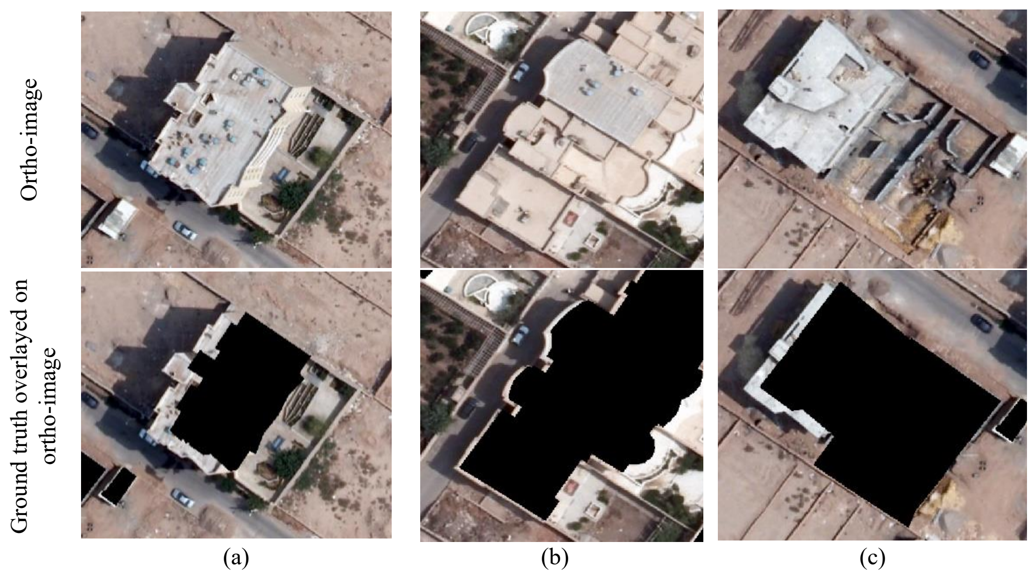


Figure 5. Examples of annotation and geometric inconsistencies affecting segmentation accuracy: (a) Orthorectification inaccuracies; (b) Architectural cantilevers; (c) Buildings under construction.

Future improvements may include incorporating true-ortho-rectified imagery, advanced pre-processing pipelines, and larger or adaptive PSO populations to further enhance performance and close the gap with state-of-the-art results. Additionally, integrating multispectral datasets and benchmarking against other segmentation models such as DeepLab or U-Net may offer further insights into the generalizability and robustness of the proposed framework.

6. Conclusions

This study introduced PSO-SAM, a hybrid segmentation framework that integrates the Segment Anything Model (SAM) with Particle Swarm Optimization (PSO) to improve segmentation performance in urban aerial imagery. The method automatically optimizes SAM’s key input parameters—points_per_side and pred_iou_thresh—to adapt its behaviour to the specific challenges of remote sensing data, such as low spatial resolution and complex urban textures.

Experimental evaluation on a 2013 ortho-image of Yazd city, Iran, demonstrated that PSO-SAM significantly outperforms the baseline SAM across all key segmentation metrics. Specifically, PSO-SAM achieved: IoU of 0.1882 (+65.5%), Precision of 0.2705 (+17.8%), Dice Coefficient of 0.3168 (+55.2%), Recall of 0.3821 (+108%), and F1-Score of 0.3168 (+55.2%). While these percentage improvements are substantial, they stem from relatively low baseline values, and absolute metrics are reported to ensure balanced interpretation.

These results highlight PSO-SAM’s ability to reduce false negatives and enhance segmentation quality, especially in the identification of complex urban structures. The substantial improvement in Recall indicates greater reliability in detecting relevant features, which is critical for applications such as urban mapping, planning, and infrastructure monitoring.

However, the absolute metric values remain lower than those reported in other domains, primarily due to: (i) Low-resolution imagery and radiometric noise, (ii) Ground truth misalignments, including Orthorectification artifacts and inclusion of ambiguous classes (e.g., buildings under construction), and (iii) Sensitivity of PSO parameters, which may affect convergence quality. These limitations underscore the difficulty of segmentation in real-world, visually complex urban environments and highlight the importance of robust pre-processing and accurate annotation.

To further improve segmentation accuracy in similar applications, future work should consider Advanced pre-processing steps, such as image denoising, super-resolution enhancement, and true Orthorectification ; Domain-specific tuning or fine-tuning of SAM, using pretraining on similar urban datasets; Comparison with alternative metaheuristics, such as Genetic Algorithms or Differential Evolution, to evaluate relative optimization efficiency; Application to higher-resolution or multispectral data, to validate generalizability and performance scalability of the proposed method. Additionally, benchmarking PSO-SAM against other segmentation models such as DeepLab or U-Net could further contextualize its strengths and limitations.

Overall, the findings demonstrate that adaptive optimization of SAM inference parameters can improve segmentation robustness in challenging urban remote sensing scenarios. Although additional validation on larger and more diverse datasets is still required, the proposed PSO-SAM framework provides a promising direction toward parameter-adaptive and training-free segmentation strategies for remote sensing applications.

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