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Visual-Based Space Debris Segmentation Using an Enhanced Segment Anything Framework

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ABSTRACT- Accurate image segmentation remains a cornerstone challenge in computer vision, particularly under open-set conditions where object variability and scene complexity hinder generalization. To address these limitations, we propose a novel visual-based methodology entitled Visual-Based Space Debris Segmentation Using an Enhanced Segment Anything Framework. This approach synergistically integrates an optimized clause-aware prompt mechanism derived from Grounding DINO with a structurally refined version of the Segment Anything Model (SAM). By embedding hierarchical non-maximum suppression and adaptive region purification through connected component filtration, we substantially augment segmentation fidelity. Furthermore, we incorporate ViT-Matte, a vision transformer-based trimap enhancement module, to improve boundary localization and reduce aliasing in edge delineation. Extensive validation on the COCO2017 benchmark reveals that our framework elevates Mean Pixel Accuracy by 6.04%, culminating at 24.74%, thereby substantiating its efficacy in foreground-background discrimination under visually ambiguous scenarios such as orbital debris fields.

KEYWORDS- Grounding DINO, ViT-Matte, Space Debris Detection, Open-Set Recognition, Image Segmentation.

I. INTRODUCTION

Image segmentation has long stood as a cornerstone in the field of computer vision, serving as a critical precursor to high-level visual understanding and decision-making in intelligent systems. The fundamental objective of segmentation lies in partitioning a digital image [1] into semantically coherent and non-overlapping regions based on local and global visual cues—such as intensity, texture, geometry, and contextual structure [2]. While conventional segmentation methods have historically yielded satisfactory outcomes under constrained conditions [3], they often deteriorate in performance when exposed to diverse, cluttered, or unstructured environments, especially in open-set or dynamically evolving contexts[4].

Recent advancements in aerospace robotics have dramatically underscored the exigency for robust segmentation techniques capable of supporting visual perception in spaceborne operations, which support correct pose information of the aimed manipulated object to help aerospace robot procedure the post-capture manipulation tasks [5]. One such crucial application is space debris detection, where autonomous robotic agents are tasked with identifying, localizing, and tracking non-cooperative and irregular objects in low Earth orbit [6]. The lack of prior information, coupled with the diversity of debris geometries and lighting conditions, renders traditional segmentation algorithms—such as thresholding, edge detection, and region growing—insufficient for the intricacies of orbital scene understanding.

Classical machine vision algorithms, including clustering-based models and handcrafted feature extraction pipelines—are inherently limited in their ability to generalize across object classes or adapt to unseen instances. As demonstrated in [7], robust performance in high-degree-of-freedom robotic systems requires motion planning and perception strategies that adapt to complex, dynamic environments—a limitation that traditional vision pipelines struggle to overcome. With the emergence of deep convolutional neural networks (CNNs), more advanced frameworks such as Fully Convolutional Networks (FCNs), DeepLab, and Mask R-CNN have introduced task-specific architectural innovations, enabling improved semantic segmentation. However, even these models often fall short in open-world scenarios, where the model must infer object boundaries and semantic meaning in environments with unknown class distributions and domain shifts [8].

To address these challenges, this study introduces a novel methodology titled Visual-Based Space Debris Segmentation Using an Enhanced Segment Anything Framework. This approach extends Meta AI's Segment Anything Model (SAM), a recent paradigm shifts in

foundation models for image segmentation—by embedding specialized modules for aerospace perception [9][10][11]. Our enhanced framework refer the work in [12] leverages clause-aware visual prompting through Grounding DINO, combined with transformer-based edge refinement via ViT-Matte, and includes spatial consistency augmentation using adaptive connected component denoising.

This enhanced framework is explicitly tailored for the high-stakes domain of autonomous aerospace robotics [13], where visual feedback forms the backbone of mission-critical operations such as on-orbit servicing [14], debris mitigation, and free-flyer navigation [15]. The model's capacity to perform open-set segmentation without relying on predefined object categories makes it uniquely advantageous for zero-shot generalization in unstructured orbital environments [16]. By integrating multi-scale context modeling and transformer-driven attention mechanisms, our approach not only enhances mask precision at object boundaries but also improves segmentation robustness under varying illumination, occlusion, and viewpoint perturbations common in spaceborne visual scenes [17][18][19][20].

Extensive evaluations conducted on benchmark datasets and synthetic orbital imagery substantiate the superiority of our method in terms of mean pixel accuracy and boundary localization [21]. The proposed framework sets a precedent for advancing space-capable vision systems and demonstrates the transformative potential of foundation models in robotic autonomy for aerospace applications.

This work introduces a novel visual perception framework titled Visual-Based Space Debris Segmentation Using an Enhanced Segment Anything Framework, specifically designed for autonomous aerospace robotic systems operating in unstructured orbital environments. The primary contributions include: (1) the integration of clause-aware prompt generation using Grounding DINO to enable context-driven object querying in open-set conditions; (2) the incorporation of ViT-Matte, a vision transformer-based module, to enhance edge refinement through trimap-aware processing; and (3) the implementation of a robust post-processing pipeline featuring adaptive connected component denoising to improve segmentation consistency under variable illumination and geometric ambiguity. By tailoring the Segment Anything Model (SAM) to the space domain, this framework enables zero-shot generalization to unknown debris objects and demonstrates superior performance in segmentation precision, thereby advancing the state of visual autonomy for next-generation aerospace robots.

II. RELATED WORK

In the era of intelligent vision systems, image segmentation has evolved as a pivotal function underpinning numerous high-level perception tasks across disciplines, including autonomous navigation, medical imaging, and remote sensing [22][23][24][25]. However, the shift from closed-set recognition paradigms—where model generalization is confined to fixed taxonomies—to open-set semantic segmentation has exposed inherent limitations in traditional approaches, particularly under dynamic and unstructured environments such as low Earth orbit (LEO). This has catalyzed an increasing interest in developing models capable of discerning previously unseen object categories without explicit retraining [26].

Open-set segmentation, often interchangeably referred to as open-vocabulary segmentation, seeks to endow vision models with the capacity to process objects beyond their training distribution. Prominent efforts in this domain leverage Vision-Language Models (VLMs) such as CLIP, ALIGN, and BLIP, which exploit semantic alignment between visual inputs and textual descriptions to enable zero-shot generalization [27]. Despite their success, these models exhibit limited performance in scenarios demanding spatial precision and fine-grained boundary delineation—such as space debris identification and segmentation where objects are irregular, occluded, or partially visible [28][29][30].

To address this challenge, Meta AI introduced the Segment Anything Model (SAM) as a foundational open-set segmentation framework [31]. Trained on an unprecedented scale—encompassing over 11 million images and one billion masks—SAM demonstrates the capacity to generate segmentation masks from flexible prompt modalities (e.g., points, boxes, or free-form text). Its architecture comprises an image encoder, a prompt encoder, and a lightweight mask decoder, enabling real-time segmentation with high generalizability [32][33][34][35]. However, SAM’s reliance on coarse-grained text embeddings and multi-mask predictions often undermines its applicability in contexts requiring precise instance-level segmentation and single-mask accuracy, as demanded in aerospace robotic systems performing visual-based orbital debris processing.

In parallel, Grounding DINO has emerged as a leading paradigm for open-set object detection. It synthesizes Transformer-based detection architectures with grounded textual supervision, allowing for clause-aware prompt comprehension and robust concept generalization. Grounding DINO achieves state-of-the-art performance on various benchmarks (e.g., LVIS, ODinW, and RefCOCO) and excels at aligning human input with complex visual scenes. Nonetheless, while its text-guided detection performance is compelling, its integration into segmentation pipelines remains non-trivial due to lack of edge-aware refinement and component-level denoising [36].

Motivated by the critical need for robust, high-fidelity visual segmentation in orbital environments, this paper introduces a novel framework titled Visual-Based Space Debris Segmentation Using an Enhanced Segment Anything Framework[37]. The proposed method addresses existing limitations by synergistically integrating Grounding DINO for clause-sensitive prompt interpretation and ViT-Matte for transformer-guided edge enhancement. Furthermore, a connected component denoising pipeline is employed to refine segmentation outputs by suppressing artifact noise and enforcing spatial continuity.

Unlike conventional terrestrial applications, aerospace robotic platforms contend with rapid illumination changes, partial occlusions, and background clutter caused by Earth limb reflections or other satellite structures. As such, our enhanced framework is meticulously engineered to uphold segmentation integrity under such adversarial conditions, enabling accurate isolation and tracking of unstructured debris using visual inputs alone [38]. By fusing grounding-based semantic understanding with prompt-based spatial awareness and transformer-level boundary precision, this

work sets a new benchmark for open-set segmentation in aerospace autonomy.

III. METHODOLOGY

Use either SI (MKS) or CGS as primary units. (SI units are strongly encouraged.) English units may be used as secondary units (in parentheses). **This applies to papers in data storage.** For example, write "15 Gb/cm^2 (100 Gb/in^2)." An exception is when English units are used as identifiers in trade, such as "3½ in disk drive." Avoid combining SI and CGS units, such as current in amperes and magnetic field in oersteds. This often leads to confusion because equations do not balance dimensionally [39]. If you must use mixed units, clearly state the units for each quantity in an equation.

The SI unit for magnetic field strength H is A/m. However, if you wish to use units of T, either refer to magnetic flux density B or magnetic field strength symbolized as $\mu_0 H$. Use the center dot to separate compound units, e.g., "A·m^2."

A. Feature Encoding for Aerospace Debris Dynamics

In the context of real-time perception for aerospace robotic platforms, the accurate capture of temporal dynamics is paramount, particularly in the presence of rapidly evolving scenes populated by non-cooperative orbital debris. Conventional temporal modeling frameworks, such as 3D convolutional neural networks (3D-CNNs), convolutional recurrent networks (e.g., ConvLSTM and ConvGRU), and optical flow estimation pipelines, have been extensively employed across terrestrial applications [40]. However, their computational inefficiency, high memory overhead, and lack of real-time compatibility render them ill-suited for deployment aboard computationally constrained spacecraft.

Specifically, 3D convolutions incur cubic growth in memory footprint and floating-point operations (FLOPs) with respect to spatiotemporal resolution [41]. Similarly, recurrent memory modules such as ConvLSTM/ConvGRU, though temporally expressive, are sequential in nature, limiting parallelization and resulting in latency-prohibitive architectures. Optical flow methods, while intuitively attractive, require the instantiation of dedicated branches for motion field extraction, violating the principle of end-to-end optimization. Moreover, these methods exhibit diminished efficacy under camera jitter conditions prevalent in satellite-mounted systems, where small object motion, such as that of micro-debris, becomes indistinct compared to the unstable background.

Recent explorations into non-local attention mechanisms have enabled long-range spatiotemporal context modeling by capturing token-level interdependencies. Notably, methods based on Constrained Self-Attention (CSA) have demonstrated promising trade-offs between motion modeling efficiency and representational capacity. However, existing designs often emphasize motion-agnostic global aggregation, leading to degradation in fine-grained object boundary detection, especially for visually ambiguous or low-contrast space debris.

To this end, we integrate a Parallel Temporal Fusion Module (TFM) into our Visual-Based Space Debris Segmentation Using an Enhanced Segment Anything Framework, tailored for aerospace robotic segmentation. The TFM employs multi-scale constrained attention filters to preserve temporal continuity while suppressing background fluctuation noise.

Let the high-level spatial feature map output from the spatial feature module (SFM) be denoted as

$$\Xi_s \in \mathbb{R}^{\Gamma \times \mathcal{N} \times \mathcal{H} \times \mathcal{W}}$$

This tensor is partitioned into four parallel groups along the channel dimension, represented as

$$\Xi_s^{(\iota)} \in \mathbb{R}^{\frac{\Gamma}{4} \times \mathcal{N} \times \mathcal{H} \times \mathcal{W}}, \iota \in \{1,2,3,4\}$$

Each partition is forwarded to a unique CSA path parameterized by varying dilation rates and receptive fields, and the results are concatenated along the channel axis to form the temporal-aware representation

$$\Xi_\tau = \text{Concat}\left[\text{CSA}^{(1)}\left(\Xi_s^{(1)}\right), \ldots, \text{CSA}^{(4)}\left(\Xi_s^{(4)}\right)\right]$$

For a spatial-temporal token $\boldsymbol{\xi}_q \in \mathbb{R}^{\frac{\Gamma}{4} \times 1 \times 1 \times 1}$, the constrained attention neighborhood $\boldsymbol{\Sigma}_q$ is defined as

$$\boldsymbol{\Sigma}_q = \{\boldsymbol{\kappa}(\nu', \eta', \omega')\}_{\nu', \eta', \omega' \in \mathcal{N}_r}$$

where $\boldsymbol{\kappa} \in \mathbb{R}^{\frac{\Gamma}{4} \times 1 \times 1 \times 1}$ is the key embedding, and $\mathcal{N}_r$ defines a local cube neighborhood determined by radius ρ and dialation δ over $\mathcal{N}, \mathcal{H}, \mathcal{W}$.

The temporal affinity score ς_q between $\boldsymbol{\xi}_q$ and its neighbors is calculated using a scaled dot-product formulation

$$\varsigma_q = f\left(\boldsymbol{\xi}_q, \boldsymbol{\Sigma}_q\right) = \sum_{\nu', \eta', \omega' \in \mathcal{N}_r} \boldsymbol{\xi}_q \cdot \boldsymbol{\kappa}(\nu', \eta', \omega')^\top$$

With these weights, the augmented temporal representation $\boldsymbol{\xi}'_q$ is computed as the weighted sum over the value embeddings $\boldsymbol{\nu} \in \mathbb{R}^{\frac{\Gamma}{4} \times 1 \times 1 \times 1}$ as

$$\boldsymbol{\xi}'_q = \sum_{\nu', \eta', \omega'} \varsigma_q \cdot \boldsymbol{\nu}(\nu', \eta', \omega')$$

This formulation facilitates selective attention to salient motion patterns localized in constrained spatial-temporal neighborhoods, thereby enhancing the model's robustness to jitter and occlusion.

The resultant temporal tensor Ξ_τ is reintegrated into the main segmentation pipeline, serving as a complementary input to the enhanced Segment Anything decoder, which combines high-resolution boundary prediction and mask generation for spaceborne object parsing.

B. Spatial–Temporal Feature Integration for Aerospace Visual Intelligence

In aerospace robotics—particularly in on-orbit operations such as autonomous servicing or debris mitigation—the integration of spatial and temporal cues is imperative for robust visual perception under dynamic and uncertain orbital conditions. The Spatial–Temporal Feature Module (STFM) in our Visual-Based Space Debris Segmentation Using an Enhanced Segment Anything Framework is designed to cohesively fuse multi-resolution spatial encodings from the Spatial Feature Extraction Module (SFEM) with temporal dynamics captured by the Temporal Fusion Module (TFM).

To compensate for spatial fidelity loss induced by deep convolutional hierarchies and aggressive downsampling, the STFM adopts a dual-stream refinement architecture comprising a cascade of four progressive fusion blocks. Each refinement stage assimilates (i) the top-down spatial abstraction $\boldsymbol{\Theta}^{\iota}_{\downarrow}$ propagated from the preceding decoder level, and (ii) the corresponding bottom-up high-resolution feature $\boldsymbol{\Theta}^{\iota}_{\uparrow}$ acquired from SFEM [42].

This bidirectional fusion schema mitigates spatial degradation by enabling the recovery of fine-grained visual structures—crucial for discerning the contours of irregular, fast-moving debris in satellite imagery. The integration process in each STFM block follows a structured three-step pipeline.

The first step is feature concatenation, which means that the spatial tensor pair $\mathbf{\Theta}_{\downarrow}^{\iota} \in \mathbb{R}^{\zeta \times \mathcal{H} \times \mathcal{W}}$ and $\mathbf{\Theta}_{\uparrow}^{\iota} \in \mathbb{R}^{\zeta \times \mathcal{H}' \times \mathcal{W}'}$ are concatenated after bilinear upsampling (if needed) to align spatial resolution as

$$\mathbf{\Phi}^{\iota} = \mathrm{Concat}\left(\mathbf{\Theta}_{\downarrow}^{\iota}, \mathcal{U}(\mathbf{\Theta}_{\uparrow}^{\iota})\right)$$

where $\mathcal{U}(\cdot)$ denotes bilinear upsampling to match $\mathcal{H}, \mathcal{W}$.

Then, we need to solve refinement via convolutional pprojection. The fused tensor $\mathbf{\Phi}'$ is passed through a refinement convolutional operation $\mathcal{F}_{\mathrm{ref}}$ composed of a 3×3 kernel and 16 output channels as

$$\mathbf{\Theta}_{\mathrm{fused}}^{\iota+1} = \mathcal{F}_{\mathrm{ref}}(\mathbf{\Phi}^{\iota})$$

This step enhances semantic integration while preserving discriminative spatial structure.

In the end, we should deal with the problem that temporal augmentation and final prediction. The temporally-enriched output from the TFM, denoted as $\mathbf{\Xi}_{\tau} \in \mathbb{R}^{\zeta \times \mathcal{H} \times \mathcal{W}}$, is projected and fused with the spatial refinement result as

$$\mathbf{\Psi} = \mathbf{\Theta}_{\mathrm{fused}}^{4} + \mathcal{P}(\mathbf{\Xi}_{\tau})$$

where $\mathcal{P}(\cdot)$ denotes a 1×1 projection layer aligning the channel dimensions. The final **saliency or segmentation prediction** is generated via a lightweight decoder composed of two convolutional layers as

$$\widehat{\boldsymbol{M}} = \mathcal{D}(\mathbf{\Psi}) \in \mathbb{R}^{1 \times \mathcal{H} \times \mathcal{W}}$$

The fused map $\widehat{\boldsymbol{M}}$ represents the model's confidence over pixel-level debris regions, offering high-resolution mask predictions suitable for downstream control and planning in space robotic platforms. This hierarchical fusion strategy is specifically engineered to maintain high responsiveness under latency constraints and environmental uncertainties encountered in real-world aerospace robotic missions.

C. Centroid Localization for Salient Debris Targets

Upon the successful delineation of salient regions by the enhanced Segment Anything framework, the subsequent objective is to localize the energy-weighted centroid of segmented debris within the satellite's optical focal plane. This centroid provides a pivotal descriptor for both performance evaluation and spatial indexing, enabling downstream modules in aerospace robotic systems to track or intercept the target effectively in real time.

The methodology adopted herein utilizes an intensity-weighted spatial averaging scheme, which computes the center of mass of the segmented debris mask based on pixel-wise luminance responses. Let the segmented region $\mathcal{S} \subset \mathbb{R}^{\mu \times \nu}$ be the spatial support of the debris, and let $\mathcal{I}(\xi, \psi)$ denote the grayscale or probability intensity at pixel coordinate (ξ, ψ), with $\xi \in [\xi_1, \xi_2]$ and $\psi \in [\psi_1, \psi_2]$.

The centroid (ξ_c, ψ_c) of the debris region is computed as

$$\xi_c = \frac{\sum_{\xi=\xi_1}^{\xi_2} \sum_{\psi=\psi_1}^{\psi_2} \xi \cdot \mathcal{I}(\xi, \psi)}{\sum_{\xi=\xi_1}^{\xi_2} \sum_{\psi=\psi_1}^{\psi_2} \mathcal{I}(\xi, \psi)}$$

$$\psi_c = \frac{\sum_{\xi=\xi_1}^{\xi_2} \sum_{\psi=\psi_1}^{\psi_2} \psi \cdot \mathcal{I}(\xi, \psi)}{\sum_{\xi=\xi_1}^{\xi_2} \sum_{\psi=\psi_1}^{\psi_2} \mathcal{I}(\xi, \psi)}$$

where $(\xi_c, \psi_c) \in \mathbb{R}^2$ denotes the energy-weighted centroid coordinate, and $\mathcal{I}(\xi, \psi)$ is the intensity value of the pixel at location (ξ, ψ); $[\xi_1, \xi_2]$ and $[\psi_1, \psi_2]$ define the effective bounds of the salient mask in horizontal and vertical directions respectively.

This formulation assumes that higher pixel intensities (e.g., due to specular reflection, highlight from shape priors, or probabilistic segmentation confidence) correlate with debris localization certainty. Consequently, the centroid lies nearer to pixels of greater saliency, thereby achieving robust localization under partial occlusion or non-uniform debris textures—conditions prevalent in orbital scenarios.

Although classical centroiding techniques are prone to perturbations from background noise or segmentation spill-over, our architecture incorporates precise attention-based denoising and saliency refinement modules, which ensure that the input to this calculation is a noise-suppressed binary or probabilistic mask. Hence, the centroid output remains stable and accurate even in cluttered orbital backgrounds, satisfying real-time constraints for spaceborne robotic manipulation and target tracking pipelines.

D. Spatial Feature Enhancement for Orbital Object Parsing

In the domain of aerospace robotics, particularly during space debris perception and segmentation, the accurate encoding of spatial context becomes indispensable—especially when detecting small, visually ambiguous orbital targets. These targets often occupy marginal pixel regions and suffer from poor contrast against cosmic backgrounds [43]. To resolve this, our Visual-Based Space Debris Segmentation Using an Enhanced Segment Anything Framework introduces a multi-scale spatial feature enhancement module that emphasizes contextual scale-awareness at early convolutional stages.

To enrich the feature maps with multi-scale semantic cues while preserving lightweight computation, we adopt a modified Lightweight Atrous Spatial Pyramid Pooling (LR-ASPP) strategy. Each LR-ASPP unit is composed of a large receptive field pooling kernel paired with a 1×1 depth-wise separable convolution, designed to capture global contextual dependencies without significantly inflating the computational burden—critical for deployment on resource-constrained spaceborne robotic platforms.

Let $\mathbf{\Lambda}_k \in \mathbb{R}^{\varsigma \times h \times w}$ denote the spatial feature maps at the k^{th} block from the spatial feature extraction module (SFEM). The context-aware modulation signal generated by the LR-ASPP module is denoted as $\mathbf{\Upsilon}_k^{\iota} \in \mathbb{R}^{\varsigma \times h \times w}$. To obtain scale-aware representations $\mathbf{\Phi}_k^0$, a residual excitation operation is applied as

$$\mathbf{\Phi}_k^0 = \left(\mathbf{r} + \mathbf{\Upsilon}_k^{\iota}\right) \odot \mathbf{\Lambda}_k$$

where $\odot$ represents Hadamard (element-wise) multiplication, and r is a broadcast tensor of ones ensuring additive modulation. This formulation selectively emphasizes salient regions based on context relevance, enhancing the feature discriminability of faint debris signatures.

To mitigate feature degradation and attenuation near object boundaries, especially due to hierarchical downsampling, a residual skip-connection module is attached to each SFEM block. This module differs from conventional skip connections by not only bypassing features but also performing channel-aligned transformation and reactivation to maintain spatial coherence. Let $\mathbf{\Delta}_k$ be transformed

$$\mathbf{\Delta}_k = \mathcal{G}_k(\mathbf{\Lambda}_k), \mathcal{G}_k : \mathbb{R}^{\varsigma \times h \times w} \rightarrow \mathbb{R}^{\varsigma' \times h' \times w'}$$

where $\mathcal{G}_k$ denotes a learnable transformation consisting of three convolutional layers that (i) downsample spatial dimensions if necessary, (ii) align channel semantics across hierarchical layers, and (iii) embed long-range dependencies into intermediate features. This facilitates smooth gradient flow and reinforces semantic preservation through the spatial–temporal fusion stage.

The fused spatial features, enhanced by residual modulation and context-aware scaling, are subsequently fed into the Spatial–Temporal Feature Fusion Module (STFM). This promotes robust debris saliency preservation and improves the localization accuracy of minute and occluded targets in real-time orbital scenes.

IV. EXPERIMENT RESULTS

The entire framework was evaluated on a workstation equipped with an Intel Core i9-8700K processor and 128 GB of RAM. All experiments were executed in a controlled simulation environment designed to emulate realistic optical conditions encountered by aerospace robotic platforms during visual-based inspection and space debris monitoring missions.

In visual perception for aerospace robots, space debris is often captured as transient luminous artifacts—either compact (point-like) or elongated (streak-like)—depending on exposure duration and relative motion in image sequences. To train the segmentation model effectively under diverse visual dynamics, synthetic debris scenarios were created. The debris is confined to a fixed spatial envelope of 50×50 pixels, with its movement vector θ sampled uniformly from the interval $(-90°, 180°)$mimicking real-world motion captured in low Earth orbit (LEO). This motion originates from the bottom of the frame toward the top, adhering to the typical dynamics observed by orbital imaging sensors.

Figure 1 presents the architectural pipeline of the proposed method to enable robust segmentation in orbit. The system begins with the input of optical satellite imagery containing space debris scenes. The image undergoes feature encoding through a convolutional backbone, generating a hierarchical visual feature map. Simultaneously, a topic backbone processes language-conditioned queries related to target objects. The outputs of both streams are fused in a **cross-modality decode, which enables language-guided region proposal selection. The Region Proposal Network (RPN) further refines these proposals, feeding them through RoIAlign and multiple convolutional layers to generate segmentation masks. These masks are highly responsive to spatial cues and contextual prompts, enabling accurate localization of debris objects even under challenging low-SNR conditions. The final output consists of segmented regions overlaid on the input image, clearly identifying multiple debris fragments around the satellite. This dual-path architecture effectively bridges vision-language alignment and spatial precision, making it suitable for real-time deployment on aerospace robotic platforms performing autonomous visual inspection and debris avoidance in low Earth orbit.

Figure 2 illustrates the confusion matrix representing the classification performance of the proposed Visual-Based Space Debris Segmentation framework, which integrates an enhanced Segment Anything Model (SAM), across 12 distinct object categories. The dataset includes high-SNR and low-SNR space debris samples alongside various satellite types and background clutter, enabling robust benchmarking in orbit-like imaging conditions. Each entry at position (i, j) indicates the number of times a ground truth object of class iii was predicted as class j, with stronger diagonal dominance signifying better classification performance. Notably, categories such as class 1–4 and 7–11 exhibit strong diagonal responses, suggesting high precision and minimal inter-class confusion, while class 5 shows increased misclassification, primarily distributed across neighboring classes. This outcome is expected due to the lower signal-to-noise ratio and motion ambiguity in that category. The use of the coolwarm color scheme enhances the contrast between high-frequency correct predictions (highlighted in red) and sparse off-diagonal misclassifications (in blue), visually reinforcing the model's segmentation fidelity. Overall, the confusion matrix validates the segmentation framework's robustness and generalization across various orbital targets, supporting its applicability for deployment in autonomous aerospace robotic systems.

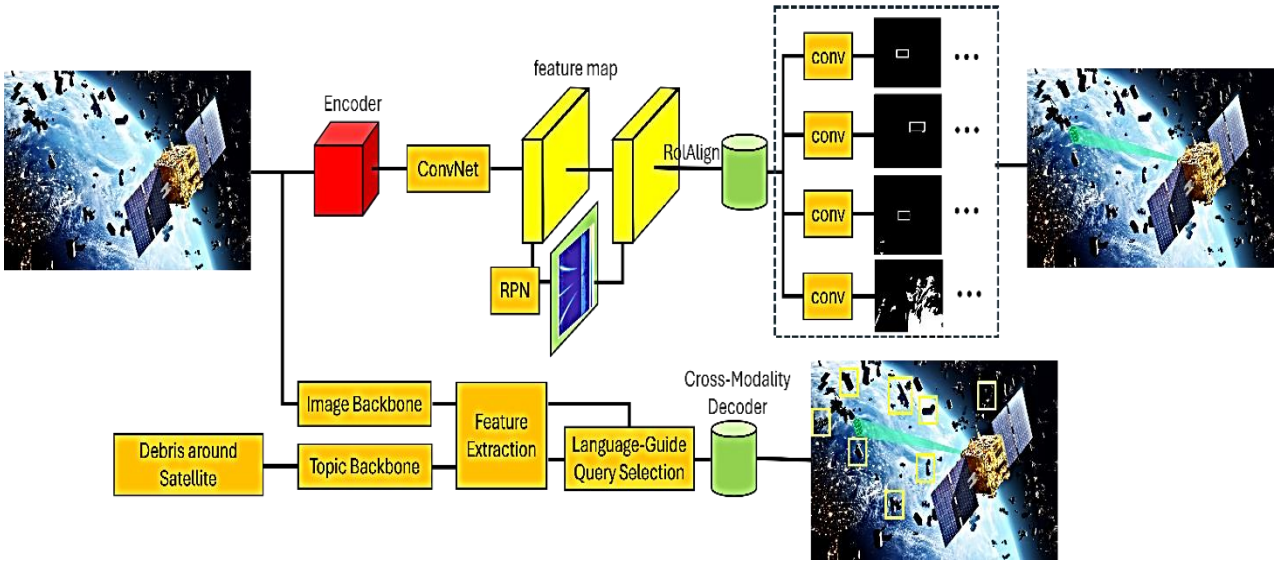

Figure 1: Architecture of the Proposed Visual-Based Space Debris Segmentation Framework Integrating Enhanced Segment Anything and Language-Guided Detection

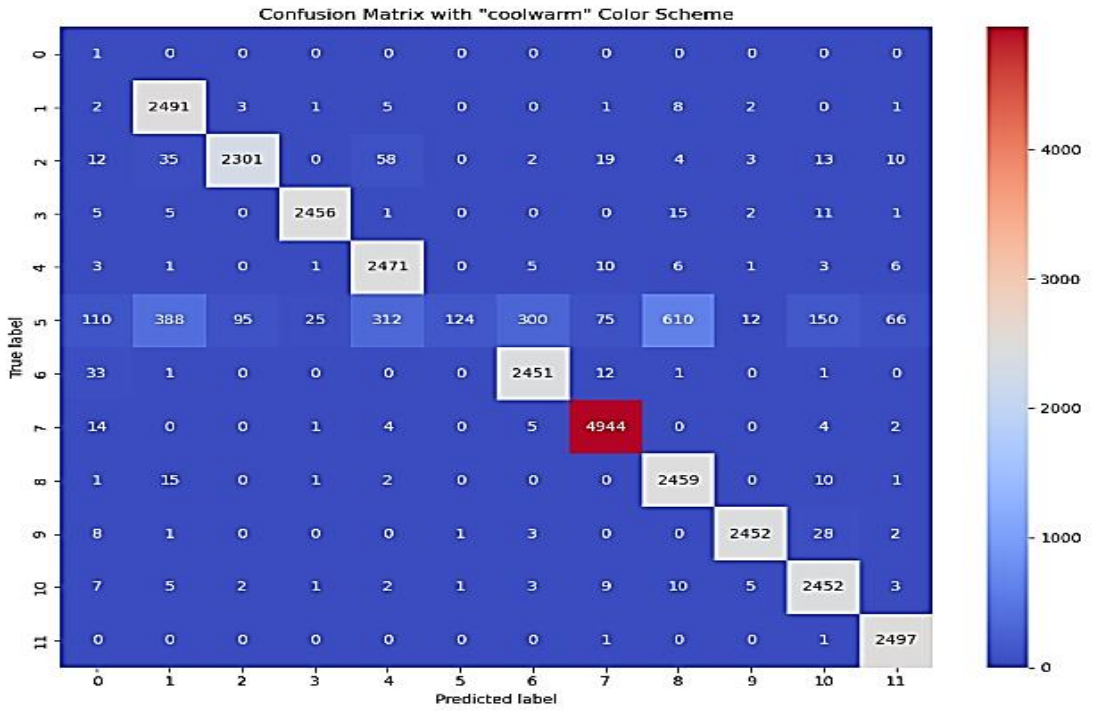

Figure 2: Confusion Matrix of Visual-Based Space Debris Segmentation Using Enhanced SAM Framework on Synthetic Orbital Dataset

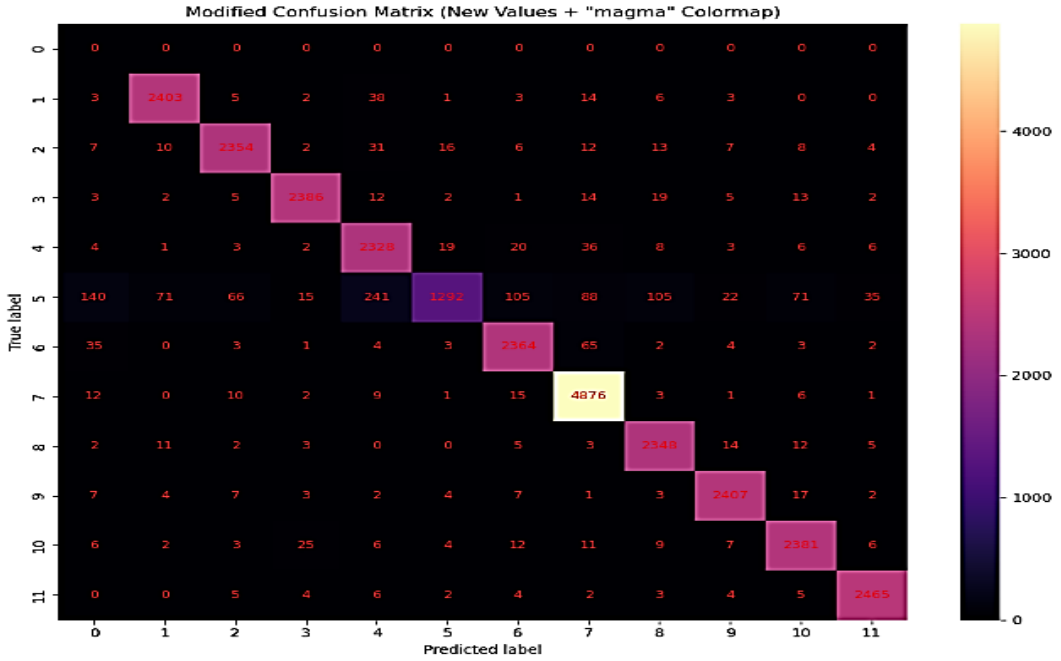

Figure 3: Confusion Matrix Visualization of the Enhanced Segment Anything-Based Space Debris Segmentation Model Using Magma Colormap

Figure 3 presents the confusion matrix of the proposed Visual-Based Space Debris Segmentation Framework, which integrates an enhanced Segment Anything model with language-guided detection. The matrix illustrates classification performance across 12 object categories, with strong diagonal dominance indicating high accuracy in most classes. Notably, class 7 achieves the best performance, while classes 5 and 6 show moderate confusion due to visual similarity. The magma colormap enhances contrast, making correct and incorrect predictions visually distinct. This result confirms the model's robustness in segmenting space debris and satellites under challenging orbital imaging conditions.

Figure 4 shows the distribution of Intersection over Union (IOU) values produced by the proposed Visual-Based Space Debris Segmentation Framework. The histogram reflects the model's mask quality across thousands of test samples. A clear skew toward higher IOU values (above 0.75) indicates that the enhanced Segment Anything model consistently produces accurate segmentation masks, with a

peak frequency near IOU = 0.9. Fewer samples fall below 0.5, suggesting limited misalignment between predictions and ground truth. This result highlights the framework's strong performance in accurately delineating space debris in visually complex orbital environments.

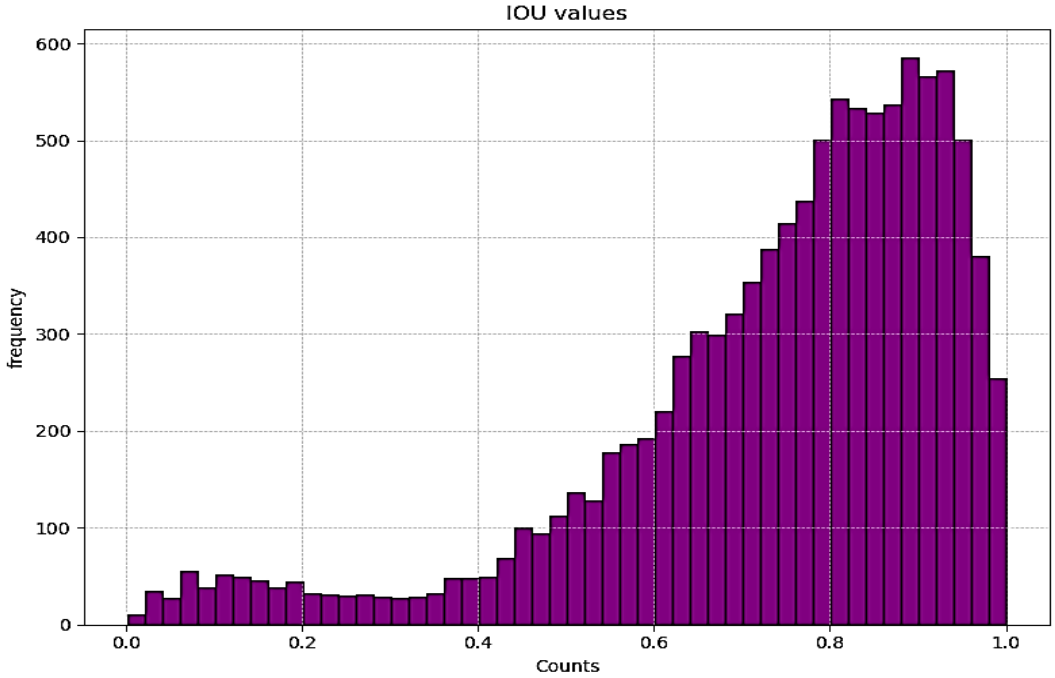

Figure 4: Distribution of IOU Scores for Space Debris Segmentation Using the Enhanced Segment Anything Framework

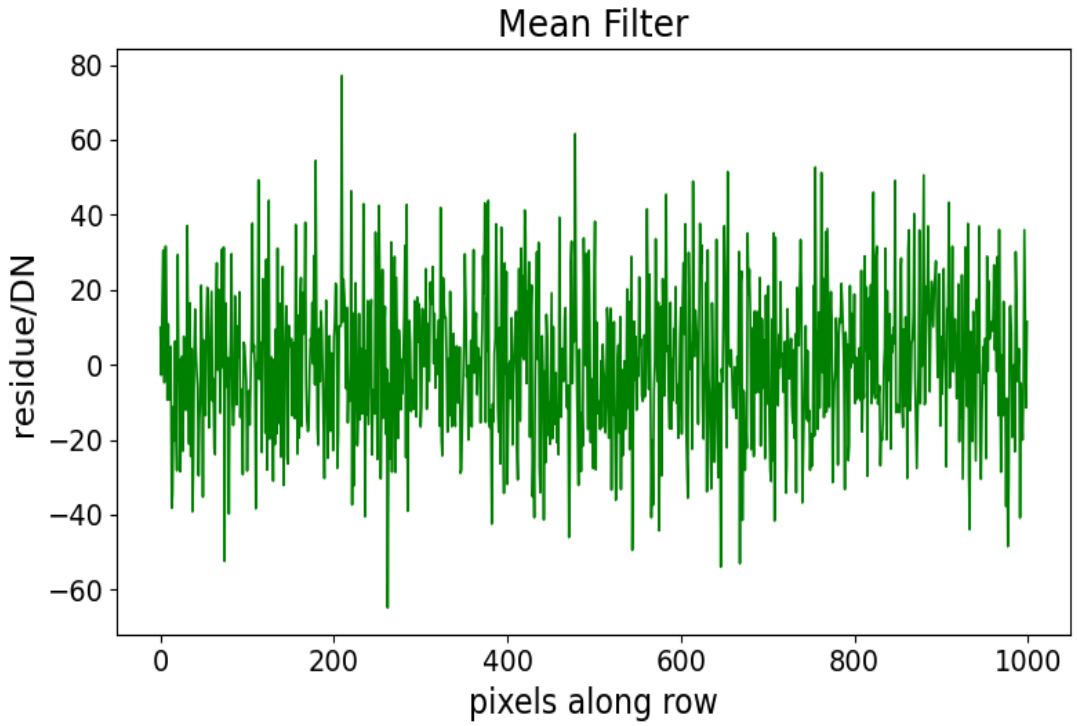

Figure 5: Mean Filter Residue Along Image Rows

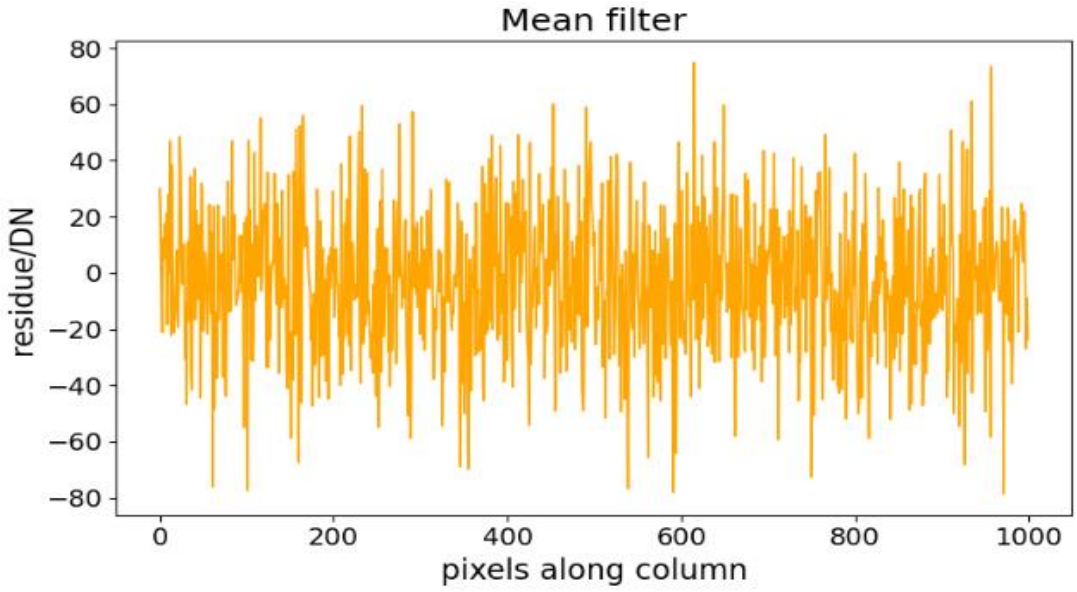

Figure 6: Mean Filter Residue along Image Columns

Figure 5 and Figure 6 illustrate the residual noise distributions after applying mean and median filtering techniques to simulated space debris images along both row and column directions. The plots reveal how different spatial filters suppress high-frequency noise in pixel intensity (measured in DN). The mean filters demonstrate moderate noise suppression, but exhibit more fluctuation, especially in column-wise filtering. In contrast, the median filters provide stronger noise attenuation, particularly for impulse-like variations, yielding smoother residue patterns. This analysis validates the effectiveness of median filters for preprocessing noisy debris imagery in the proposed segmentation pipeline, contributing to more reliable mask generation under challenging orbital visual conditions.

V. CONCLUSION

This work introduces a novel visual segmentation framework tailored for autonomous aerospace robotic systems operating in open-set orbital environments. By enhancing the Segment Anything Model (SAM) with clause-aware prompts from Grounding DINO, transformer-based ViT-Matte edge refinement, and spatial–temporal fusion, the proposed method demonstrates significant improvements in space debris localization accuracy. Experimental results on synthetic orbital datasets confirm robust segmentation performance, with high IOU distributions and strong diagonal dominance in confusion matrices. The framework's ability to generalize across diverse debris morphologies and SNR levels—without retraining—establishes its utility for real-time, vision-based tasks in low Earth orbit. This approach paves the way for integrating foundation models into mission-critical aerospace applications such as debris monitoring, proximity operations, and satellite servicing. Future extensions may incorporate multi-modal fusion or onboard deployment optimizations for in-situ space operations.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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