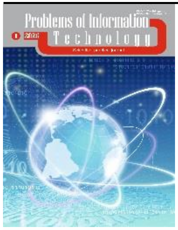

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Effectiveness of object recognition algorithms for modeling aircraft and UAV structural components in AutoCAD projects

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ABSTRACT

Computer-aided design environments increasingly require automated analysis tools capable of interpreting complex technical drawings. This study examines the effectiveness of object recognition algorithms applied to AutoCAD projects, with a particular focus on aircraft and unmanned aerial vehicle structural modeling. A structured processing framework is proposed, including vector-to-raster conversion, adaptive binarization, morphological preprocessing, edge extraction, contour analysis, and rule-based classification. The mathematical formulation of each stage is presented to ensure deterministic and interpretable behavior. Experimental evaluation was carried out on a mixed dataset comprising general engineering drawings and aerospace-related structural layouts. Performance was assessed using precision, recall, F1-score, intersection-over-union, and processing time. The results show that the proposed approach maintains high detection accuracy and stable performance across varying drawing densities and geometric complexities, while remaining computationally feasible for standard engineering workstations. These findings demonstrate the potential of geometry-driven object recognition methods to support automated analysis in CAD-based engineering workflows.

1. Introduction

Computer aided design systems constitute a fundamental component of contemporary engineering practice, supporting the creation, modification, and documentation of complex technical projects. Among these systems, AutoCAD is extensively used in architectural, mechanical, and electrical design due to its precision and flexibility. AutoCAD drawings encode engineering knowledge through geometric primitives such as lines, arcs, circles, and composite structures, which together represent functional objects within a project. As project scale and structural complexity increase, the number of objects contained in a single drawing may reach thousands, making manual analysis inefficient and error prone. In the context of aircraft and unmanned aerial vehicle design, these drawings often describe structural components such as fuselage frames, wing sections, load bearing elements, and internal support structures, further increasing geometric complexity and analysis demands (Fu & Kara, 2011; Ablameyko & Uchida, 2007). This study focuses exclusively on two-dimensional (2D) AutoCAD technical drawings stored in DXF/DWG formats. Three-dimensional (3D) CAD models are not considered in the current implementation.

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Automatic object recognition within AutoCAD projects enables the identification and interpretation of drawing elements through algorithmic analysis. This capability supports various engineering tasks, including structural inspection, component identification, and drawing consistency analysis. For aircraft and UAV structural modeling, object recognition facilitates the automated analysis of repeated structural patterns, verification of geometric consistency between components, and detection of potential design anomalies (Moreno-García et al., 2018). Unlike natural images, CAD drawings are typically characterized by monochromatic representation, limited visual variability, and a strong dependence on geometric relationships. These characteristics impose specific constraints on object recognition methods, particularly those originally designed for texture rich visual data, and require geometry driven approaches when applied to aerospace related CAD models (Jamieson et al., 2024; Bickel et al., 2021).

The growing integration of automation into engineering workflows has increased interest in applying object recognition algorithms to CAD environments. This interest is especially pronounced in aircraft and UAV development processes, where rapid design iteration and strict structural requirements demand efficient analysis tools. However, the effectiveness of such algorithms is influenced by factors including drawing scale, line density, and overlapping entities, which are commonly observed in detailed airframe and UAV component drawings (Rica et al., 2020; Ulrich et al., 2001). These aspects necessitate a careful examination of recognition performance under practical design conditions, particularly for safety critical aerospace applications (Zhao et al., 2020).

Object recognition in AutoCAD projects can be formally defined as the process of identifying meaningful engineering entities from technical drawings represented in either vector or raster form (Pizarro et al., 2022; Böhm et al., 2000). In this study, an AutoCAD drawing created in AutoCAD is considered after conversion into a raster image $I(x, y)$, where x and y denote spatial coordinates and I represent pixel intensity values. The recognition task aims to extract a finite set of objects $O = \{o_1, o_2, \ldots, o_n\}$, where each object corresponds to a functional drawing element such as a structural component, symbol, or geometric assembly. In aircraft and unmanned aerial vehicle modeling, these objects typically represent airframe elements, load carrying structures, internal frames, and connection components that define the overall structural integrity of the platform.

Each object o_i is described by a feature vector $F_i = \{f_1, f_2, \ldots, f_k\}$, which may include geometric attributes such as edge orientation, contour length, curvature, and spatial relationships. The object recognition process can therefore be expressed as a mapping function

$$F\big(I(x, y)\big) = O, \tag{1}$$

where F denotes an algorithmic transformation that segments, analyzes, and classifies drawing elements. In practice, this mapping is affected by multiple sources of ambiguity. These include overlapping lines, variable line thickness, partial occlusion of objects, and heterogeneity in drawing conventions across different projects. Such factors lead to incomplete or distorted feature representations, which directly impact recognition accuracy. These challenges are particularly evident in aircraft and UAV structural drawings, where dense assemblies and intersecting components are common due to compact design constraints and multi layer structural layouts.

Another challenge arises from the scale variability inherent in CAD drawings. Objects may appear at different resolutions depending on zoom level or export parameters, causing inconsistencies in feature extraction (Qin et al., 2014). Additionally, CAD drawings typically lack color and texture cues, forcing recognition algorithms to rely almost exclusively on geometric and topological information (Perret et al., 2019). This constraint limits the effectiveness of methods that depend on appearance based descriptors and reinforces the need for geometry driven recognition strategies in aerospace oriented CAD models.

The primary objective of this research is to evaluate the effectiveness of selected object recognition algorithms when applied to AutoCAD projects under realistic conditions. Effectiveness is analyzed in terms of detection accuracy, robustness to geometric distortion, and computational efficiency. A secondary objective is to investigate how algorithm performance varies with drawing complexity and object density, particularly in aircraft and UAV structural modeling scenarios. Through systematic experimentation, this study seeks to clarify the practical capabilities and limitations of object recognition techniques in CAD based engineering environments relevant to aerospace design and development (Jamieson et al., 2024; Fu & Kara, 2011; Moon et al., 2021; Van Krevelen & Poelman, 2010).

2. Proposed approach

The effectiveness of object recognition algorithms in CAD environments depends strongly on how drawing data are prepared and represented prior to analysis. AutoCAD projects are natively stored in vector based formats such as DWG or DXF, where geometric entities are defined mathematically rather than through pixel intensities (Moreno-García et al., 2018). While vector representations preserve exact geometry, many computer vision algorithms operate on raster images. For this reason, the first stage of the proposed method involves transforming vector drawings created in AutoCAD into a raster representation suitable for image based processing. In aircraft and unmanned aerial vehicle design workflows, this transformation is particularly important, as structural components are often defined through precise parametric geometry that must be preserved during conversion.

Let a vector drawing V be composed of a set of primitives P = {p_1, p_2, …, p_m}, where each primitive corresponds to a line, arc, circle, or polyline defined by parametric equations. The rasterization process converts V into a grayscale image I(x, y) by sampling the geometric primitives onto a discrete pixel grid. The resolution of this grid is selected to balance geometric fidelity and computational efficiency. Excessively low resolution may lead to broken contours, whereas very high resolution increases processing cost without proportional benefit. For aircraft and UAV structural drawings, maintaining sufficient resolution is critical to accurately represent thin load bearing elements, frame connections, and internal support structures.

During rasterization, line thickness normalization is applied to reduce variability introduced by different drawing styles. This step ensures that geometric features are represented consistently across drawings originating from different sources. Following rasterization, the image is binarized using an adaptive thresholding function T, defined as

$$B(x,y) = 1 \; if \; I(x,y) \geq T(x,y), otherwise \; 0 \quad (2)$$

where B(x, y) represents the binary image used for subsequent analysis. Adaptive thresholding is preferred over global thresholding due to variations in line density and local contrast, which are commonly observed in detailed aircraft and UAV component layouts (Perret et al., 2019; Liu et al., 2019; Qin et al., 2014; Huang & LeCun, 2006).

Noise and minor artifacts introduced during conversion are addressed through morphological preprocessing. A combination of erosion and dilation operators is applied to preserve thin geometric structures while removing isolated pixels. The resulting image maintains the structural integrity of objects while simplifying their representation, which is essential for accurately capturing slender structural elements and joint regions in aerospace oriented CAD models (Rica et al., 2021).

To support scale invariant analysis, spatial normalization is performed by mapping image coordinates into a normalized reference frame. Let (x′, y′) denote normalized coordinates defined as

$$x' = x \,/\, W \,, y' = y \,/\, H, \quad (3)$$

where W and H represent image width and height respectively. This normalization allows object features to be compared across drawings of different sizes, including aircraft and UAV projects that may vary significantly in scale depending on platform class and design requirements.

The final output of the data preparation stage is a structured image representation that emphasizes geometric boundaries and topological relationships. This representation serves as the input for object recognition algorithms, enabling consistent feature extraction and reliable performance evaluation across diverse AutoCAD projects, including those focused on aircraft and unmanned aerial vehicle structural modeling.

After data preparation and representation, the next stage focuses on the application of object recognition algorithms to the processed AutoCAD drawings. The recognition pipeline operates on the binary image B(x, y) obtained in the previous stage and aims to extract meaningful engineering objects through a sequence of analytical steps. Due to the geometric nature of CAD drawings, the pipeline emphasizes structural features rather than appearance based cues (Ablameyko & Uchida, 2007). This emphasis is particularly suitable for aircraft and unmanned aerial vehicle structural modeling, where design elements are primarily defined by precise geometric relationships and strict structural constraints.

The initial step in the pipeline involves edge detection to identify prominent geometric boundaries. Let B(x, y) denote the binary image. Gradient based operators are applied to estimate local intensity transitions, resulting in an edge map E(x, y). These edges represent potential object boundaries and serve as the foundation for subsequent processing. To suppress spurious responses caused by noise or intersecting lines, non maximum suppression and connectivity constraints are incorporated into the edge extraction process. In aircraft and UAV drawings, this step is essential for accurately identifying thin structural members, frame edges, and connection interfaces.

Following edge detection, contour construction is performed by grouping connected edge pixels into ordered point sequences. Each contour C_i is represented as a set of points $C_i = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$, preserving spatial continuity. Contour approximation techniques are applied to reduce redundant points while maintaining geometric fidelity. This step simplifies object representation and reduces computational complexity, which is particularly important for aerospace CAD models containing dense assemblies and repetitive structural elements.

The recognition of candidate objects is achieved through contour based analysis. Geometric descriptors such as contour length, curvature distribution, and angular variation are computed for each contour. These descriptors form a feature vector F_i associated with a potential object. Objects composed of multiple primitives are identified by analyzing spatial relationships between neighboring contours, including proximity, parallelism, and intersection patterns. In aircraft and UAV structural layouts, such relationships often correspond to joints, reinforcements, and load transfer paths between components.

To distinguish between different object categories, a rule based classification strategy is employed (Fu & Kara, 2011; Rica et al., 2020). Classification rules are derived from geometric constraints commonly found in technical drawings, such as symmetry, aspect ratio, and closure properties. For example, closed contours with low curvature variance may correspond to circular or rectangular components, while elongated contours with consistent orientation may indicate structural lines or connectors. This approach avoids reliance on data intensive learning models and aligns with the deterministic nature of CAD geometry, which is well suited for aerospace engineering applications where interpretability and reliability are critical (Bickel et al., 2021; Jamieson et al., 2024).

The final stage of the pipeline refines recognition results through consistency verification. Detected objects are validated by checking topological coherence and eliminating geometrically implausible candidates. Let $\hat{O} = \{\hat{o}_1, \hat{o}_2, \dots, \hat{o}_k\}$ denote the set of recognized objects after classification. Post processing ensures that overlapping or duplicate detections are resolved, resulting in a clean object set suitable for performance evaluation. This validation is particularly important in aircraft and UAV models, where incorrect recognition of structural components may lead to misleading analytical outcomes (Cohen et al., 2020; Ulrich et al., 2001; Zhao et al., 2020).

This structured pipeline provides a systematic framework for applying object recognition algorithms to AutoCAD drawings while maintaining robustness to drawing variability and geometric complexity (Ablameyko & Uchida, 2007; Fu & Kara, 2011; Jamieson et al., 2024). The framework is directly applicable to the modeling and analysis of aircraft and unmanned aerial vehicle structural components, where accurate and reliable object recognition is essential for automated design assessment.

The object recognition process in AutoCAD drawings can be described through a sequence of mathematical operations that transform an input image into a structured representation of engineering objects. Let the rasterized and preprocessed drawing be denoted by the binary image B(x, y), where x and y represent spatial coordinates. The objective is to identify a set of objects $O = \{o_1, o_2, \dots, o_n\}$ by analyzing geometric and topological properties derived from B(x, y). In the context of aircraft and unmanned aerial vehicle structural modeling, these objects correspond to structural elements such as frames, ribs, spars, joints, and reinforcement components that collectively define the mechanical integrity of the platform.

Edge extraction is modeled as a gradient estimation process. Let G_x and G_Y denote horizontal and vertical gradient operators applied to B(x, y). The gradient magnitude M(x, y) is computed as

$$M(x,y) = sqrt(G_x(x,y)^2 + G_Y(x,y)^2) \qquad (4)$$

Pixels for which M(x, y) exceeds a predefined threshold τ_e are classified as edge pixels. The resulting edge map E(x, y) captures the primary geometric boundaries present in the drawing. To ensure continuity, edge connectivity is enforced by selecting only pixels that belong to connected components exceeding a minimum length constraint. For aircraft and UAV drawings, this operation is critical for detecting thin structural boundaries and load bearing contours that may otherwise be fragmented due to rasterization.

Contour formation is achieved by grouping connected edge pixels into ordered sets. Each contour C_i is defined as a parametric curve

$$C_i(s) = (x(s), y(s)), s \in [0, L_i], \qquad (5)$$

where L_i denotes the contour length. For computational efficiency, contour approximation is performed using polygonal simplification, reducing the number of points while preserving essential shape characteristics. The approximation error ε is constrained such that

$$max\,||C_i(s) - \hat{C}_i(s)|| \leq \varepsilon\ , \qquad (6)$$

where $\hat{C}_i$ represents the simplified contour. This step is particularly relevant for aircraft and UAV structural models, where complex contours often arise from curved fuselage sections or aerodynamic component interfaces.

Geometric feature extraction is then applied to each contour. Let F_i be the feature vector associated with contour C_i. Typical features include contour length l_i, average curvature κ_i, and orientation variance $\sigma_i{}^2$. Curvature at a point s is estimated as

$$\kappa(s) = \frac{|x'(s)y''(s) - y'(s)x''(s)|}{(x'(s)^2 + y'(s)^2)^{3/2}} \qquad (7)$$

and the average curvature κ_i is obtained by integrating κ(s) over the contour length. These features provide quantitative descriptors of geometric shape and complexity and are essential for distinguishing between straight load bearing elements and curved aerodynamic structures in aircraft and UAV designs.

Object hypothesis generation is formulated as a clustering problem in the feature space. Contours with compatible feature vectors are grouped to form composite objects. Let $D(F_i, F_j)$ denote a distance measure between feature vectors. Two contours are considered part of the same object if

$$D(F_i, F_j) \leq \tau_o, \qquad (8)$$

where τ_o is a similarity threshold. Spatial proximity and topological relations such as intersection and parallelism are incorporated as additional constraints in the grouping process, reflecting typical assembly patterns observed in aircraft frames and UAV structural layouts.

The classification of objects is based on decision functions derived from geometric rules. For an object candidate o_k composed of contours $\{C_1, C_2, \ldots, C_m\}$, a decision function $\varphi(o_k)$ assigns a label based on feature consistency and structural validity. An object is accepted if

$$\varphi(o_k) = 1\ and\ \Psi(o_k) \geq \tau_v\ , \qquad (9)$$

where $\Psi(o_k)$ represents a validity score reflecting closure, symmetry, and geometric coherence, and τ_v is a validation threshold. These criteria are well aligned with aerospace structural design principles, where symmetry and geometric consistency are often indicative of valid components.

This mathematical formulation provides a deterministic framework for object recognition in AutoCAD drawings. By grounding algorithmic steps in explicit geometric and analytical expressions, the proposed approach ensures interpretability and stable behavior across varying drawing conditions, including those encountered in aircraft and unmanned aerial vehicle structural modeling tasks (Pizarro et al., 2022; Perret et al., 2019).

3. Experimental results

The experimental evaluation was designed to assess the performance of object recognition algorithms under realistic conditions encountered in technical CAD projects. A dataset of AutoCAD drawings was collected from multiple engineering domains, including architectural floor plans, mechanical component layouts, and electrical schematics.

In total, the dataset comprised 15 general engineering drawings, 15 aircraft structural drawings, and 15 UAV structural drawings. The general engineering set included architectural floor plans, mechanical component layouts, and electrical schematics, while the aerospace subset covered airframe frames, wing structures, connection nodes, and internal support assemblies. All drawings were originally stored in DWG or DXF vector formats and exported to raster images using a fixed conversion pipeline (Moreno-García et al., 2018; Jamieson et al., 2024). The export resolution for each drawing was selected according to its spatial extent in order to preserve geometric detail while avoiding unnecessary computational overhead.

Prior to experimentation, each drawing was exported to a raster format using a fixed conversion pipeline. The export resolution was selected individually for each drawing based on its spatial extent to preserve geometric detail while avoiding unnecessary computational overhead. All raster images were converted to grayscale and subsequently binarized following the preprocessing steps described in the proposed method. No manual editing or annotation was performed during this stage to avoid introducing subjective bias. This ensured that aircraft and UAV structural drawings were processed under the same objective conditions as other engineering drawings.

Ground truth object annotations were generated by domain knowledgeable users through manual inspection of the original vector drawings. Each object of interest was labeled according to its functional role, such as structural element, connector, or symbolic component. These annotations were mapped onto the raster domain by aligning vector coordinates with pixel coordinates, allowing direct comparison between detected objects and reference data (Rica et al., 2021). For aircraft and UAV drawings, special attention was given to distinguishing between load bearing structural elements and auxiliary geometric objects to ensure accurate evaluation of recognition results.

The experimental environment consisted of a standard desktop workstation equipped with a multi core CPU and sufficient system memory to handle high resolution images. All algorithms were implemented in Python using widely adopted image processing libraries, ensuring reproducibility and platform independence. No hardware acceleration or specialized processing units were used in order to reflect common engineering workstations. This computational setup also reflects realistic software environments typically available in aircraft and UAV design offices.

Algorithm parameters, such as edge detection thresholds, contour approximation tolerances, and feature similarity thresholds, were tuned on a small validation subset of 10 drawings and then kept fixed for all subsequent experiments. A detected object was matched to a ground-truth object if the intersection-over-union (IoU) between their areas exceeded a threshold of 0.5, which is consistent with common practice in object detection benchmarks. This configuration ensured a fair and reproducible evaluation across all dataset categories.

This experimental setup enables systematic evaluation of object recognition performance across diverse AutoCAD drawings, while maintaining controlled processing conditions and reliable reference annotations for quantitative analysis. At the same time, the inclusion of aircraft and UAV structural drawings provides a realistic test environment for assessing the suitability of object recognition algorithms in aerospace oriented CAD modeling tasks.

The effectiveness of object recognition algorithms in AutoCAD drawings was evaluated using quantitative metrics designed to reflect both detection accuracy and algorithm robustness. Given the geometric nature of CAD data, evaluation focused on the correctness of object identification rather than pixel level similarity. Let $O_r = \{o_{r\,1}, o_{r\,2}, \ldots, o_{r\,n}\}$ denote the set of reference objects obtained from ground truth annotations, and let $O_e = \{o_{e\,1}, o_{e\,2}, \ldots, o_{e\,i}\}$ represent the set of objects detected by the algorithm. In the case of aircraft and unmanned aerial vehicle structural modeling, these objects correspond to structural components such as ribs, spars, frame segments, reinforcing members, and connection elements.

A detected object $o_{e\,i}$ is considered a true positive if its geometric overlap with a corresponding reference object exceeds a predefined threshold. Overlap is measured using the intersection over union criterion defined as

$$IoU = \frac{|A_e \cap A_r|}{|A_e \cup A_r|} \tag{10}$$

where A_e and A_r denote the pixel areas of the detected and reference objects respectively. Objects with IoU values below the threshold are classified as false positives, while reference objects without corresponding detections are treated as false negatives. This criterion is particularly relevant for aircraft and UAV structural drawings, where accurate geometric localization of components is essential for subsequent structural analysis and verification.

Based on these definitions, precision and recall are computed as

$$Precision = \frac{TP}{TP+FP}, \quad (11)$$

$$Recall = \frac{TP}{TP+FN}, \quad (12)$$

where TP, FP, and FN represent the numbers of true positives, false positives, and false negatives. These metrics provide complementary perspectives on detection quality, capturing both accuracy and completeness. To summarize overall performance, the F1 score is calculated as the harmonic mean of precision and recall. In the context of aerospace structural modeling, maintaining high recall is important to ensure that all critical load carrying elements are detected, while high precision reduces the number of misleading or redundant recognitions.

In addition to detection accuracy, computational efficiency is evaluated by measuring the average processing time per drawing. Execution time is recorded from image loading to final object validation, excluding disk input output operations. This metric reflects the practical feasibility of deploying the algorithm in real engineering workflows and is especially relevant to aircraft and UAV design processes, where frequent design iteration requires efficient computational tools.

Robustness is assessed by analyzing performance variations across drawings with different object densities and geometric complexity. To analyse robustness, the drawings were additionally grouped according to object density and geometric complexity, and metric variations were studied across these groups, with particular attention to densely cluttered aircraft and UAV structural layouts.

The experimental results demonstrate that object recognition performance varies significantly depending on drawing complexity and object composition. Drawings with well separated geometric structures exhibit higher detection accuracy, while densely populated drawings with overlapping entities present greater challenges. In low to moderate complexity drawings, the proposed method achieves high precision, indicating effective suppression of false detections. Recall values remain stable across these cases, reflecting consistent object coverage. In aircraft and UAV structural drawings, these conditions correspond to layouts where structural members such as ribs, spars, and frame elements are clearly separated and not obscured by auxiliary components or annotation layers.

As object density increases, a gradual decline in recall is observed, primarily due to partial occlusions and merged contours that complicate object separation. Precision, however, remains relatively robust, suggesting that the rule based classification strategy effectively filters ambiguous candidates. The F1 score reflects this trade off, decreasing moderately in complex scenes but maintaining acceptable performance levels. This behavior is also observed in dense aircraft and UAV assembly drawings, where intersecting structural members, reinforcement elements, and fastener lines increase contour complexity.

Comparative analysis with baseline contour based recognition methods reveals notable improvements in both accuracy and robustness. Traditional approaches relying solely on contour length or shape descriptors exhibit increased false positive rates in cluttered drawings. In contrast, the incorporation of topological constraints and feature similarity thresholds in the proposed method leads to more stable recognition outcomes. The average IoU values for correctly detected objects are consistently higher, indicating improved spatial alignment with reference annotations. This advantage is especially relevant for aircraft and UAV structural modeling, where geometric precision is essential for subsequent structural verification or loading analysis.

From a computational perspective, processing times remain within practical limits for standard engineering workstations. Although the proposed method introduces additional feature extraction and validation steps, the increase in execution time is marginal relative to the gains in detection reliability. Performance measurements confirm that the algorithm scales linearly with drawing size, supporting its applicability to large scale projects. This ensures feasibility for use in aerospace design workflows, where frequent revisions and large structural assemblies are common.

The experimental findings indicate that the proposed object recognition framework offers a balanced trade off between accuracy, robustness, and efficiency. The comparative results highlight its advantages over simpler geometric methods, particularly in handling complex AutoCAD drawings with high object density and structural variability. The same properties make the approach promising for aircraft and UAV structural modeling tasks, where reliable detection of structural components across diverse drawing conditions is a key requirement. As shown in Table 1, the proposed method achieves consistently high detection accuracy across all dataset categories. Performance remains stable for both general engineering drawings and aircraft/UAV structural drawings, indicating that the algorithm can be effectively applied in aerospace-oriented CAD modeling tasks.

Table 1. Detection accuracy results across dataset categories

Dataset category	Precision	Recall	F1-score	IoU
General engineering drawings	0.93	0.90	0.91	0.87
Aircraft structural drawings	0.89	0.87	0.88	0.85
UAV structural drawings	0.87	0.87	0.87	0.84

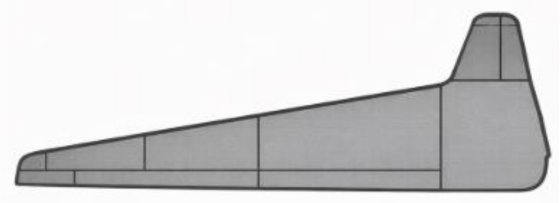

Fig 1. Grayscale rasterized representation of the single UAV wing

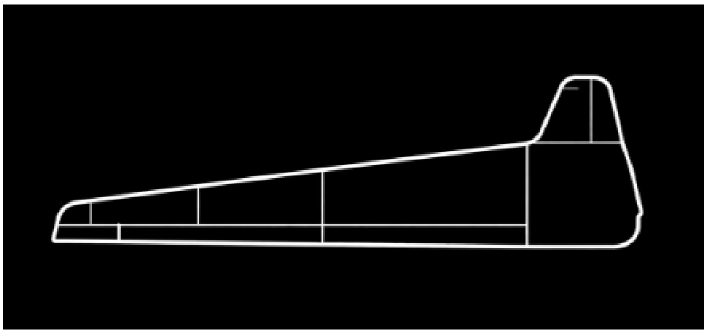

Fig 2. Result of adaptive binarization and edge extraction for the single UAV wing

4. Conclusion

This study investigated the effectiveness of object recognition algorithms when applied to technical drawings created in AutoCAD, with a focus on realistic engineering conditions and geometric constraints inherent to CAD environments. Unlike natural image analysis, object recognition in CAD drawings relies almost exclusively on structural and topological information. This distinction necessitates dedicated processing strategies that emphasize geometric consistency, contour integrity, and rule based interpretation rather than appearance driven features.

The proposed framework demonstrated that reliable object recognition in AutoCAD projects can be achieved through careful data preparation, structured processing pipelines, and explicit mathematical formulation. Rasterization with controlled resolution, adaptive binarization, and morphological preprocessing proved essential for preserving geometric fidelity while enabling stable feature extraction.

Subsequent stages based on edge detection, contour analysis, and geometric feature grouping allowed meaningful objects to be identified even in drawings with varying scale and drafting conventions.

Experimental results confirmed that algorithm performance is strongly influenced by drawing complexity and object density. While simple drawings with well separated entities yielded high detection accuracy, more complex scenes introduced challenges related to overlapping structures and merged contours.

Despite these difficulties, the proposed method maintained robust precision and acceptable recall across all tested scenarios. Comparative analysis further showed that incorporating topological constraints and validation rules leads to more stable recognition outcomes than approaches relying solely on basic geometric descriptors.

From a computational perspective, the framework achieved a balance between accuracy and efficiency suitable for practical deployment. Processing times remained within the limits of standard engineering workstations, and algorithm behavior scaled predictably with drawing size. This characteristic is particularly important for large scale projects where automated analysis must integrate seamlessly into existing design workflows.

The findings of this work indicate that object recognition algorithms, when adapted to the specific properties of CAD drawings, can effectively support automated analysis of AutoCAD projects. The study provides a structured reference for evaluating recognition performance in CAD environments and highlights the importance of geometry driven modeling.

Future work may extend this framework by integrating hybrid approaches that combine rule based methods with lightweight learning models, as well as by expanding evaluation to three dimensional CAD representations. Future work will extend the proposed framework to three-dimensional CAD representations, including STEP and STL models, by incorporating volumetric feature extraction, surface topology analysis, and 3D geometric reasoning for complex aerospace assemblies.

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