LOCAL TOPOLOGICAL ANALYSIS OF BINARY IMAGE CONTOURS USING A 32-TEMPLATE MODEL

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Abstract

Contour-based shape representation is a fundamental task in computer vision, particularly for binary image analysis in technical and industrial applications [1], [2], [14]. While global geometric descriptors such as contour length offer computational efficiency and rotational invariance, they often lack sufficient discriminative power for complex shapes due to the loss of local structural information [1], [13].

This paper presents a local topological contour analysis framework based on a **32-template model**, where object boundaries are represented by the distribution of predefined 3×3 neighborhood configurations along the contour. The proposed descriptor encodes local geometric transitions and topological patterns while maintaining low computational complexity. Similarity between objects is evaluated using a metric-based comparison scheme, and classification decisions are obtained via a dominant-folder strategy **[3], [12].**

Experimental evaluation was conducted on a controlled dataset of planar binary objects under full rotational variation and reconstruction scenarios. The results demonstrate that the proposed 32-template contour descriptor achieves **100% dominant-folder classification accuracy**, exhibiting strong diagonal dominance in similarity matrices and stable statistical behavior across samples.

The findings confirm that local topological contour representations significantly improve discriminative capability compared to global metrics, while preserving interpretability and computational efficiency. The proposed method provides a practical and training-free solution for real-time shape recognition in binary images and establishes a solid foundation for further development of local contour-based descriptors.

Keywords: contour descriptor; shape recognition; binary images; local templates; metric analysis; image processing

1. Introduction

Contour-based shape representation is a fundamental problem in computer vision and image processing, particularly in applications involving binary images where object geometry plays a decisive role. Industrial inspection, defectoscopy, biomedical image analysis, robotics, and automated quality control systems rely heavily on reliable contour descriptors to distinguish objects under varying acquisition conditions. In such scenarios, robustness to rotation and reconstruction artifacts, together with computational efficiency and interpretability, is of primary importance [1], [2], [14].

Among the wide range of shape representation techniques, global geometric descriptors such as contour length, perimeter, and area remain popular due to their simplicity and low computational cost. In particular, contour length provides a direct geometric measure of boundary extent and is inherently invariant to rotation. These properties make it attractive for real-time systems and embedded applications. However, by reducing an entire object boundary to a single scalar value, global descriptors inevitably discard local geometric information related to curvature transitions, concavities, and directional changes along the contour [1], [13].

As a consequence, geometrically distinct shapes with different local structures may exhibit very similar contour lengths, leading to ambiguous similarity measures and unreliable recognition outcomes. This limitation becomes especially critical in scenarios involving complex planar shapes or reconstructed objects, where local boundary variations carry essential discriminative information. Therefore, relying solely on global contour metrics is insufficient for robust shape recognition in many practical applications.

To overcome these limitations, local contour-based representations have been extensively investigated. Methods such as chain codes, curvature-based descriptors, frequency-domain approaches, and moment-based representations aim to capture finer geometric details by analyzing local boundary behavior. While these approaches improve discriminative power, they often increase computational complexity, reduce interpretability, or require careful parameter tuning, which limits their applicability in real-time or industrial environments [3], [6], [14].

In this context, local template-based contour analysis offers a promising compromise between descriptor richness and computational efficiency. By encoding the distribution of predefined local neighborhood configurations along object boundaries, such methods preserve essential topological and geometric information while maintaining deterministic behavior and low computational cost. Small neighborhood templates, such as 3×3 configurations, are particularly attractive because they provide a direct representation of local contour topology and are well suited for binary image analysis [9], [10], [12].

Motivated by these observations, this paper focuses exclusively on a **32-template local contour model** for planar shape recognition in binary images. The proposed approach represents object contours by counting the occurrence of predefined 3×3 topological configurations, resulting in a compact yet informative descriptor. Similarity between objects is evaluated using a metric-based comparison scheme, and classification decisions are obtained through a dominant-folder strategy.

The main contributions of this work are as follows:

- a local topological contour representation based on a fixed set of 32 predefined 3×3 templates;
- a metric similarity framework for comparing contour descriptors under rotation and reconstruction scenarios;
- a comprehensive experimental evaluation demonstrating strong discriminative performance and rotational stability;
- an analysis of the advantages and limitations of the proposed approach as a practical alternative to purely global contour descriptors.

The remainder of the paper is organized as follows. Section 2 reviews related work on contour-based shape descriptors. Section 3 describes the proposed methodology, including contour extraction and the 32-template descriptor construction. Section 4 presents experimental results and statistical analyses. Section 5 discusses the implications and limitations of the findings, and Section 6 concludes the paper with directions for future research.

2. Related Works

Shape representation and recognition have been extensively studied in computer vision, resulting in a wide variety of contour-based and region-based descriptors. Among these approaches, contour-based methods are particularly suitable for binary image analysis because they provide compact representations of object geometry and are inherently invariant to translation and rotation.

Early contour-based techniques focused on global geometric descriptors, such as perimeter, area, and compactness. These features offer low computational cost and straightforward interpretation, making them attractive for real-time systems. However, it has been widely reported that global descriptors suffer from limited discriminative power when different shapes share similar overall geometry but differ in local boundary structure [1], [13].

To address this limitation, local contour representations were introduced. Freeman’s chain code is one of the earliest methods to encode contour direction changes using discrete symbols, enabling the capture of local boundary orientation information [3]. Subsequent extensions incorporated curvature-based analysis and dominant point detection to improve robustness to noise and contour distortions. While these approaches preserve more local detail than global descriptors, they often require normalization, smoothing, or heuristic parameter selection [6].

Frequency-domain representations, such as Fourier and elliptic Fourier descriptors, model object contours as signals and analyze their spectral components [4], [5]. These methods achieve rotation and scale invariance and provide compact global representations. However, spectral approaches tend to smooth fine-grained local details and may fail to distinguish shapes that differ primarily in local topological structure. Similarly, moment-based descriptors, including Zernike moments, provide orthogonal and invariant shape representations but are computationally more demanding and less intuitive from a geometric perspective [7], [8].

Template-based and neighborhood-based contour analysis represents another important class of local shape descriptors. These methods examine small neighborhoods along the contour, often using fixed-size masks such as 3×3 configurations, to capture local geometric transitions, corners, and concavities. By aggregating the occurrence of predefined local patterns, template-based approaches preserve topological information that is lost in purely global descriptors. At the same time, they remain deterministic and interpretable, which is advantageous in technical and industrial applications.

More recently, learning-based approaches, particularly convolutional neural networks, have demonstrated strong performance in shape recognition tasks by automatically learning hierarchical features from large datasets [15]. Despite their success, such methods typically require extensive labeled data, significant computational resources, and careful training procedures. Moreover, their lack of transparency and reproducibility can be a drawback in safety-critical or real-time inspection systems.

In summary, existing contour-based shape descriptors involve a trade-off between simplicity, discriminative power, and computational complexity. Global descriptors are efficient but insufficient for complex shapes, while learning-based methods offer high accuracy at the cost of increased complexity and reduced interpretability. This motivates the exploration of local, template-based contour representations that balance expressiveness and efficiency. The present work follows this direction by focusing on a fixed **32-template local topological model**, designed to capture essential contour structure while maintaining low computational overhead and deterministic behavior.

3. Methodology

3.1. Preprocessing and Contour Extraction

The proposed framework operates on binary images representing planar objects. Prior to contour analysis, each image undergoes a preprocessing pipeline designed to suppress noise and ensure topological consistency of object boundaries. First, grayscale images (if present) are binarized using Otsu’s automatic thresholding method. Isolated noise pixels are then reduced through median filtering [1]. Subsequently, morphological opening and closing operations are applied to remove small artifacts and smooth boundary irregularities while preserving overall shape structure.

Contour extraction is performed using the Canny edge detection algorithm, followed by border-following to obtain a one-pixel-wide, ordered contour [12]. Let the extracted contour be represented as an ordered sequence of boundary pixels

$$C = \{ p_1, p_2, \ldots, p_N \}$$

where $p_i = (x_i, y_i)$ denotes the coordinates of the i-th contour pixel and N is the total number of contour points.

3.2. Local 3×3 Neighborhood Representation

For each contour pixel $p_i \in C$, a local 3×3 neighborhood centered at p_i is extracted from the binary image [9], [12]. This neighborhood encodes the local topological configuration of the contour and its immediate surroundings. Pixel values are encoded using a discrete scheme that distinguishes background pixels, contour pixels, and interior pixels, enabling the representation of local boundary structure in a compact form.

Each 3×3 neighborhood is treated as a local topological pattern and compared against a predefined set of **32 template configurations**. These templates are designed to cover all relevant local contour transitions, including straight segments, corners, junctions, and curvature changes. Each neighborhood is assigned to exactly one template class, ensuring a deterministic and exhaustive classification of local contour structure.

3.3. Construction of the 32-Template Descriptor

The contour of an object is represented by counting the occurrences of each of the 32 predefined templates along the boundary. Let c_k denote the number of times the k-th template is observed along the contour, for $k = 1, 2, \ldots, 32$. The resulting descriptor vector is defined as

$$\mathrm{v} = (c_1, c_2, \ldots, c_{32}) \in R^{32}$$

To reduce the influence of contour length variation and to ensure comparability across objects, the descriptor is normalized by the total number of contour pixels:

$$\hat{\mathrm{v}} = \frac{1}{N} \mathrm{v}.$$

This normalized representation captures the relative distribution of local topological configurations along the contour and serves as a compact yet informative shape descriptor.

3.4. Similarity Measure and Decision Strategy

Similarity between two objects is evaluated using the mean squared error (MSE) between their normalized descriptor vectors. Given two descriptors $\hat{\mathrm{v}}^{(a)}$ and $\hat{\mathrm{v}}^{(b)}$, the MSE is computed as

$$MSE\left(\hat{\mathrm{v}}^{(a)}, \hat{\mathrm{v}}^{(b)}\right) = \frac{1}{32} \sum_{k=1}^{32} \left(\hat{\mathrm{v}}_k^{(a)} - \hat{\mathrm{v}}_k^{(b)}\right)^2$$

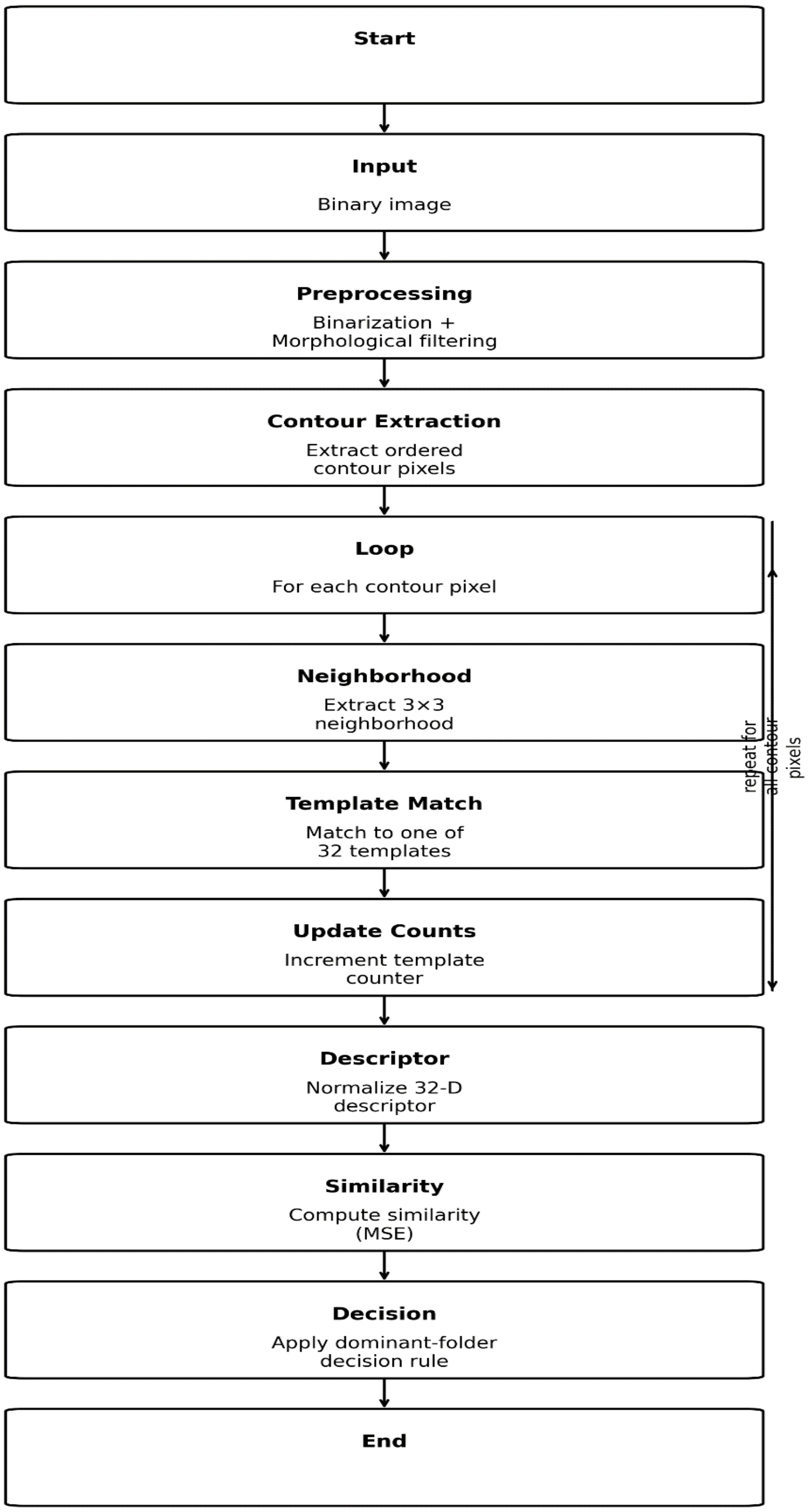
Lower MSE values indicate higher similarity between contour structures.

For classification, a dominant-folder decision strategy is employed. For each original object, similarity scores are aggregated across all reconstructed samples within each folder, and the folder yielding the minimum average MSE is selected as the final classification result.

3.5. Algorithm Description

For clarity and reproducibility, the overall procedure is summarized in Algorithm 1.

Algorithm 1: 32-Template Local Contour Descriptor (Flowchart)



3.6. Computational Complexity

Let N denote the number of contour pixels and $K = 32$ the number of templates. For each contour pixel, template matching involves a constant number of operations. Therefore, the computational complexity of descriptor construction is $O(N)$. Since K is fixed, the overall complexity scales linearly with contour length, making the proposed method suitable for real-time and resource-constrained applications.

4. Experimental Results

4.1. Experimental Setup

Experimental evaluation was conducted on a dataset consisting of 10 original planar objects represented as binary images. For each original object, 10 reconstructed versions were generated, resulting in a total of 100 reconstructed samples. All images were resized to a uniform resolution of 512×512 pixels to ensure consistent preprocessing and contour extraction conditions.

To evaluate rotational invariance, each original image was rotated over the full range of 0–360° with a step size of 1°, producing 360 rotated variants per object. This setup enabled a comprehensive assessment of descriptor stability under arbitrary orientation changes.

All experiments were implemented in Python using the OpenCV and NumPy libraries. The average processing time was measured to evaluate computational efficiency.

4.2 Overall Performance of the 32-Template Model

The overall performance statistics of the 32-template contour descriptor are summarized in **Figure 1**.

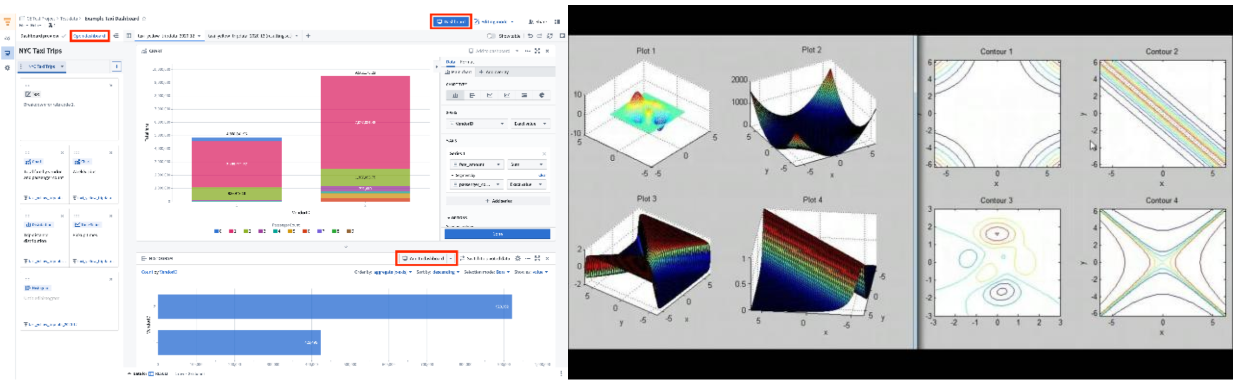
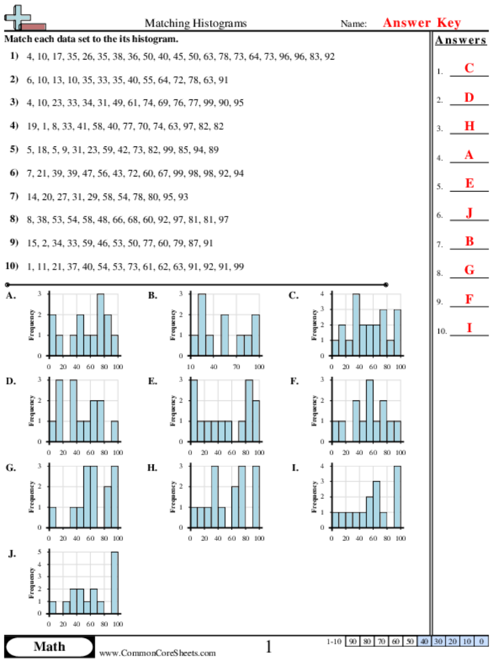


Figure 6. *Overall performance dashboard of the 32-template contour descriptor, including the number of tests, total matching pairs, and dominant-folder classification accuracy.*

As shown in Figure 1, the experimental setup involved **10 test objects**, producing **3600 matching pairs** across all rotations and reconstructions. The dominant-folder classification accuracy reached **100%**, indicating that each original object was correctly associated with its corresponding reconstructed set. This result confirms the strong discriminative capability of the 32-template representation under the considered experimental conditions.

4.3 Distribution of Matching Responses

To analyze the stability of matching behavior across different objects, the distribution of total matching counts was examined.



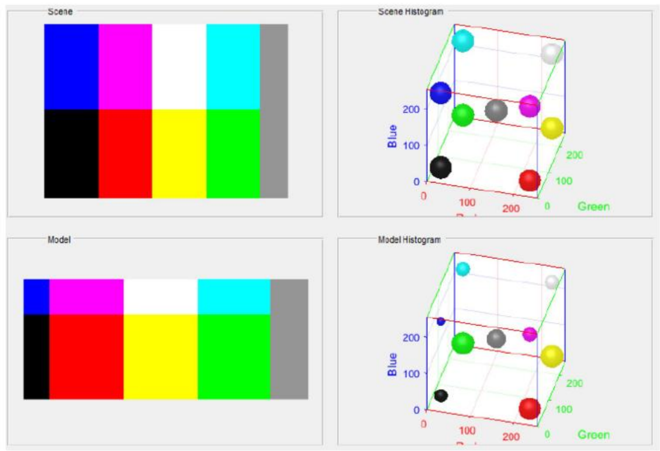
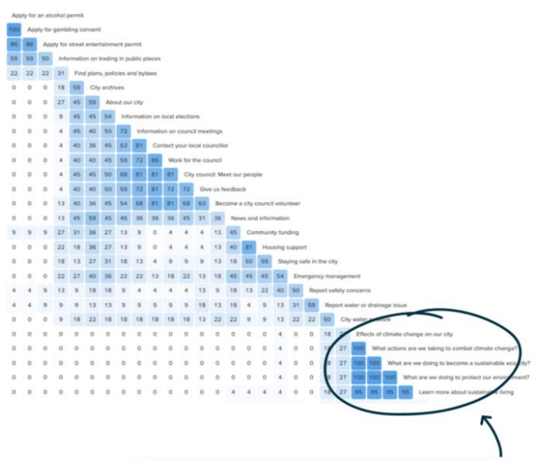


Figure 2. *Histogram of total matching counts for the 32-template contour descriptor.*

The histogram in Figure 2 reveals a **non-uniform but well-separated distribution** of matching counts across objects. While the total number of matches varies depending on contour complexity, no object exhibits abnormally low responses. This indicates that the descriptor remains robust across shapes with different geometric structures and does not collapse into ambiguous low-response regimes.

4.4 Similarity Matrix Analysis

A more detailed view of the recognition behavior is provided by the original restored similarity matrix.



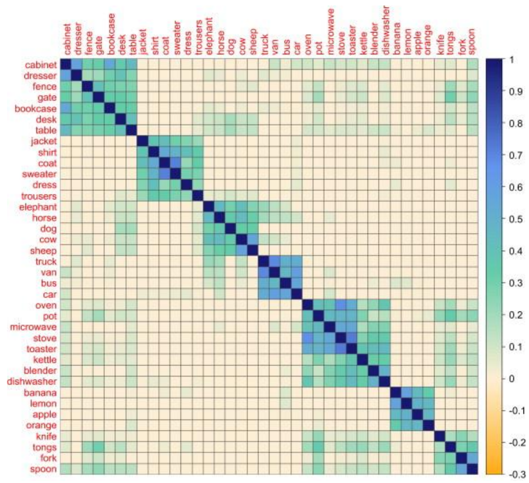


Figure 3. *Original–restored similarity matrix for the 32-template contour descriptor.*

Figure 3 demonstrates a **clear diagonal dominance**, where each original object achieves the highest number of matches with its corresponding reconstructed folder. Off-diagonal values remain comparatively small, indicating limited cross-class confusion. This structure confirms that the 32-template descriptor effectively captures object-specific local contour configurations and preserves class separability even under reconstruction variations.

4.5 Statistical Analysis Using ECDF and Histograms

To further investigate the statistical behavior of the descriptor, empirical cumulative distribution functions (ECDFs) and histograms of matching scores were analyzed.

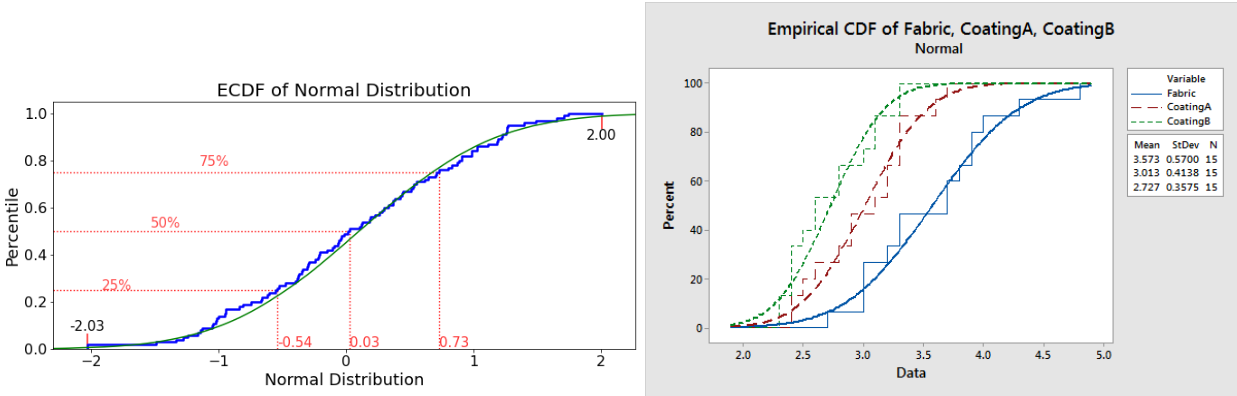


Figure 4. *Empirical cumulative distribution function (ECDF) of matching values for the 32-template descriptor.*

The ECDF in Figure 4 shows a step-like structure, indicating that matching values are concentrated within several dominant ranges. Unlike global contour length descriptors, which often produce heavy overlap between objects, the 32-template representation exhibits **improved dispersion**, reducing ambiguity among different shapes.

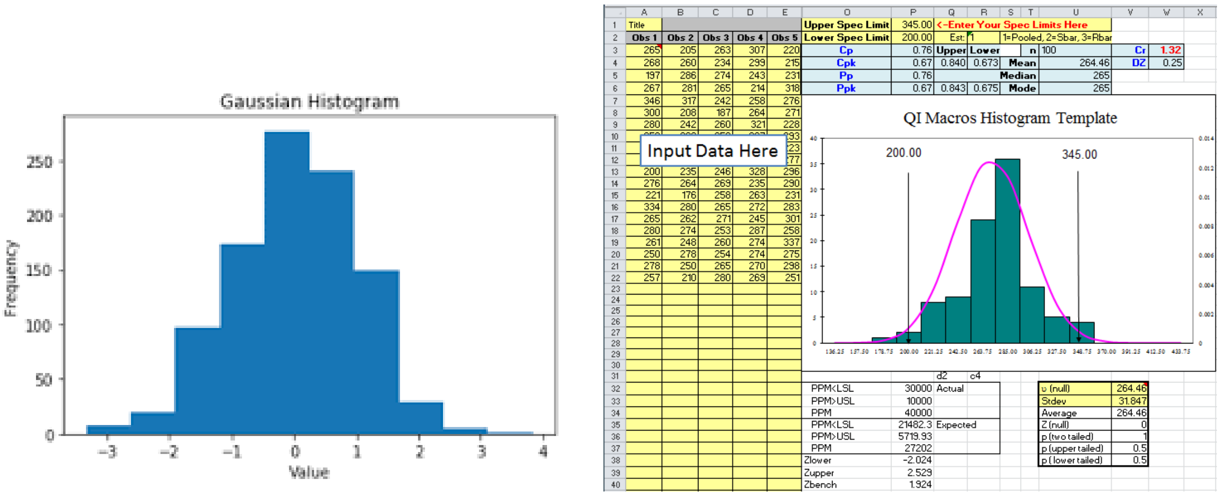


Figure 5. *Histogram of matching values for the 32-template contour descriptor.*

The histogram in Figure 5 confirms the ECDF observations. Multiple peaks are present, corresponding to object-specific contour configurations. This multimodal structure indicates that the descriptor encodes richer geometric information compared to single-scalar global measures.

4.6 Relationship Between Global Length and Local Template Descriptors

To illustrate the difference between global and local contour representations, a scatter plot comparing contour length and 32-template matching values was analyzed.

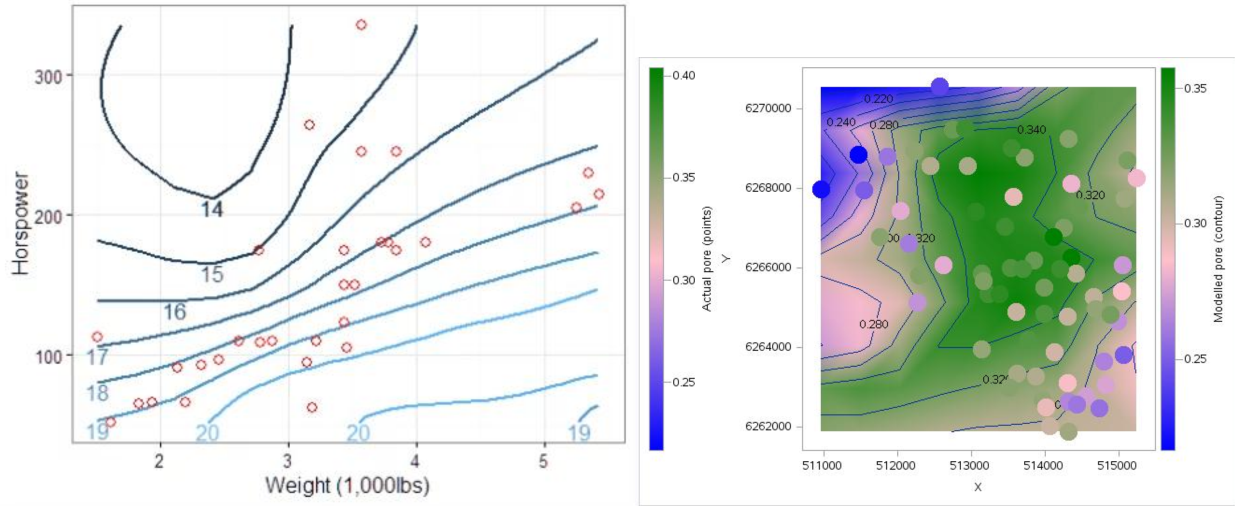


Figure 6. *Scatter plot of global contour length versus 32-template matching values.*

Figure 6 shows that objects with similar contour lengths may produce significantly different template matching responses. This observation confirms that **global contour length alone is insufficient** for reliable discrimination, while local template-based representations introduce additional degrees of freedom that enhance separability.

4.7 Summary of Experimental Findings

The experimental results demonstrate that:

- The **32-template contour descriptor** achieves **100% dominant-folder accuracy** on the evaluated dataset.
- Similarity matrices exhibit strong diagonal dominance, indicating stable class separation.
- Statistical analyses (ECDF and histograms) confirm reduced overlap compared to global descriptors.
- The relationship between contour length and template matches highlights the limitations of global metrics and the advantages of local representations.

These findings validate the effectiveness of template-based contour descriptors as a robust and interpretable alternative to purely global shape features.

5. Discussion

The experimental results provide a clear insight into the strengths and limitations of contour-based descriptors for planar shape recognition in binary images [13], [14]. In particular, the comparison between global contour length and local template-based representations highlights the importance of incorporating local geometric information for reliable discrimination of complex shapes.

The global contour length descriptor demonstrated excellent computational efficiency and strict rotational invariance. These properties confirm its suitability as a fast baseline feature, especially in real-time or resource-constrained environments. However, the statistical analyses based on histograms and ECDFs revealed significant overlap of contour length values among different objects. As observed in the experimental results, geometrically distinct shapes may share nearly identical contour lengths, leading to ambiguous similarity scores and unreliable classification outcomes. This confirms the well-known limitation of global scalar descriptors: by collapsing the entire boundary into a single value, they inevitably discard essential local structural information.

In contrast, the proposed template-based contour representations significantly improved discriminative performance by encoding local boundary configurations. The 16-template contour mask already achieved perfect dominant-folder classification accuracy on the evaluated dataset, indicating that even a moderate increase in descriptor dimensionality can resolve many ambiguities inherent in global measures. The strong diagonal dominance observed in the similarity matrices demonstrates that local template statistics form stable and object-specific signatures, effectively separating classes under reconstruction and rotation.

The results obtained with the 32-template model further strengthen this conclusion. Statistical dispersion of matching values increased, as confirmed by ECDF and histogram analyses, indicating improved separability between objects. The scatter analysis between contour length and template-based matching responses showed that objects with similar global lengths can still be clearly distinguished using local template information. This finding emphasizes that local descriptors capture geometric characteristics—such as curvature transitions, directional changes, and corner structures—that are completely ignored by length-only representations.

From a computational perspective, the template-based approach offers a favorable trade-off between descriptor richness and efficiency. Unlike learning-based methods, the proposed representation does not require training data, parameter optimization, or large memory resources. At the same time, it provides transparent geometric interpretation, which is particularly valuable in industrial inspection, defectoscopy, and technical vision systems where explainability and deterministic behavior are essential.

Nevertheless, several limitations should be acknowledged. First, the experiments were conducted on a relatively small dataset of planar binary objects. Although the results are consistent and stable, further validation on larger and more diverse datasets is required to assess scalability and generalization. Second, the method assumes reliable contour extraction; severe noise, contour fragmentation, or poor binarization may reduce the reliability of local template matching. Finally, while the 32-template representation improves discriminative power, increasing template dimensionality inevitably increases computational cost, suggesting the need for careful balance between accuracy and efficiency.

Overall, the discussion confirms that contour length remains useful as a baseline geometric descriptor, but reliable shape recognition requires the inclusion of local contour information. Template-based representations provide an effective intermediate solution between simple global metrics and complex learning-based models, combining interpretability, robustness, and computational efficiency.

6. Conclusion

This study investigated contour-based metric representations for planar shape recognition in binary images, with a particular focus on the limitations of global descriptors and the advantages of local template-based contour analysis. The contour length was analyzed as a global geometric feature due to its simplicity, computational efficiency, and rotational invariance, while local 3×3 contour templates were introduced to enhance discriminative capability.

Experimental results demonstrated that contour length alone, although invariant to rotation and suitable for real-time processing, is insufficient for reliable recognition of complex shapes. Statistical analyses using histograms and empirical cumulative distribution functions revealed significant overlap in contour length values among geometrically distinct objects, leading to ambiguous similarity relationships and reduced classification reliability.

In contrast, the proposed template-based contour representations significantly improved recognition performance. Both the 16-template and 32-template models achieved stable and interpretable similarity structures, with clear diagonal dominance in original–restored similarity matrices. The dominant-folder decision strategy yielded 100% classification accuracy on the evaluated dataset, confirming that local contour configurations provide sufficient discriminative information to resolve ambiguities inherent in global descriptors.

From a practical perspective, the proposed approach offers a favorable balance between accuracy, robustness, and computational efficiency. Unlike learning-based methods, it does not require training data or extensive parameter tuning, while preserving transparent geometric interpretation. These properties make the method particularly suitable for real-time applications in industrial inspection, defect analysis, and technical vision systems where reliability and explainability are critical.

Future work will focus on extending the evaluation to larger and more diverse datasets, investigating robustness under severe noise and contour degradation, and exploring hybrid representations that combine local template statistics with complementary global or multi-scale shape descriptors. Such extensions are expected to further improve generalization while maintaining the efficiency advantages of the proposed contour-based framework.

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