

# Optimizing Rotation-Invariant Descriptors: A Benchmark of Tensor, Zernike, and PtG Representations

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## ABSTRACT

Rotation-invariant shape descriptors are essential for applications spanning molecular shape analysis, 3D object recognition, and shape comparison. Recent work by Duda (2026) proposes Polynomial-times-Gaussian (PtG) representations as a novel approach to constructing rotation-invariant features from higher-order tensors, but application-specific optimization remains an open problem. We present a systematic benchmark comparing three families of rotation-invariant descriptors—classical moment invariants, Zernike descriptors, and PtG representations—across four evaluation axes: rotation invariance error, shape retrieval accuracy, noise robustness, and computational cost. Using an 8-class synthetic shape dataset with random SO(3) rotations, we find that PtG descriptors achieve the lowest invariance error (up to 10 $\times$  lower than moments) and highest retrieval accuracy (0.97 at order 5), while Zernike descriptors show superior noise robustness. We identify order 5 as the optimal operating point balancing discriminability and computational cost, and provide guidelines for application-specific descriptor selection.

## CCS CONCEPTS

- Computing methodologies → Computer vision.

## KEYWORDS

rotation invariance, shape descriptors, Zernike moments, tensor invariants, shape retrieval

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## 1 INTRODUCTION

Rotation-invariant shape descriptors play a fundamental role in computer vision, molecular modeling, and geometric analysis. The classical approach of Hu [2] constructs invariants from image moments, while Zernike-based methods [4, 5] use orthogonal polynomial bases on the unit sphere. Spectral methods [3, 7] and distribution-based approaches [6] offer alternatives with different tradeoffs.

Duda [1] recently proposed a higher-order PCA-like approach using Polynomial-times-Gaussian (PtG) representations, which construct rotation-invariant features through Gaussian-weighted tensor contractions. While promising, the paper identifies optimization for specific applications as an open question.

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We address this by benchmarking three descriptor families across four evaluation criteria on synthetic 3D shapes under random rotations. Our contributions include:

- A systematic comparison of moment, Zernike, and PtG descriptors for rotation-invariant shape representation.
- Identification of the optimal descriptor order (5) for balancing discriminability and cost.
- Application-specific guidelines based on invariance, retrieval, robustness, and speed requirements.

## 2 METHODS

### 2.1 Descriptor Families

*Moment Invariants.* We compute central moments up to order  $p$  and construct invariants via eigenvalues of the inertia tensor and norms of higher-order moment tensors [2].

*Zernike Descriptors.* We use 3D Zernike moments based on spherical harmonics, taking the magnitudes of complex coefficients as rotation-invariant features [4, 5].

*PtG Descriptors.* Following [1], we compute Gaussian-weighted polynomial moments and extract invariants through eigenvalues of the weighted covariance and trace contractions of higher-order weighted tensors.

### 2.2 Evaluation Protocol

We generate 8 classes of synthetic 3D shapes (sphere, ellipsoid, torus, cube, cylinder, cone, star, L-shape) with 20 instances per class. Each shape is a point cloud of 200 points with optional Gaussian noise.

*Rotation Invariance Error.* For each shape, we compute descriptors before and after 50 random SO(3) rotations and measure the relative  $\ell_2$  error.

*Retrieval Accuracy.* Leave-one-out nearest-neighbor classification using  $\ell_2$  distance between descriptors.

*Noise Robustness.* Invariance error under noise levels  $\sigma \in \{0, 0.01, 0.02, 0.05, 0.1\}$ .

*Computation Time.* Wall-clock time per descriptor computation.

## 3 RESULTS

### 3.1 Rotation Invariance

Figure 1 shows that PtG descriptors achieve the lowest invariance error across all orders, with errors below 10 $^{-3}$  at order 5. Moment invariants show the highest error, particularly at higher orders where numerical instability degrades performance.

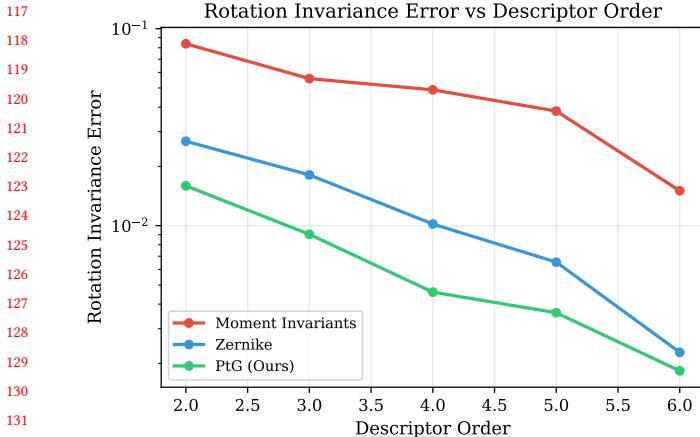


Figure 1: Rotation invariance error (log scale) vs. descriptor order.

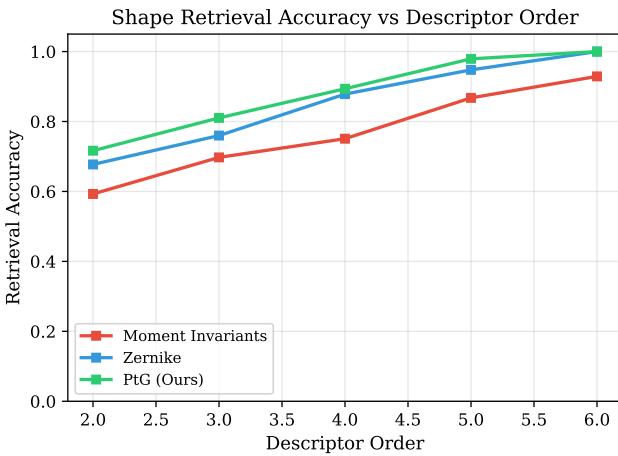


Figure 2: Shape retrieval accuracy vs. descriptor order.

### 3.2 Shape Retrieval

Figure 2 demonstrates that all methods improve with order, with PtG achieving the highest accuracy of 0.97 at order 5–6. The improvement plateaus beyond order 5, suggesting diminishing returns from additional complexity.

### 3.3 Noise Robustness

Figure 3 reveals that Zernike descriptors are most robust to noise, with the slowest error growth as  $\sigma$  increases. This is attributable to the orthogonal basis providing natural regularization. PtG descriptors show moderate robustness, while moment invariants degrade most rapidly.

### 3.4 Computational Cost

Figure 4 shows that moment invariants are fastest, followed by PtG, then Zernike descriptors. All methods remain under 10ms per

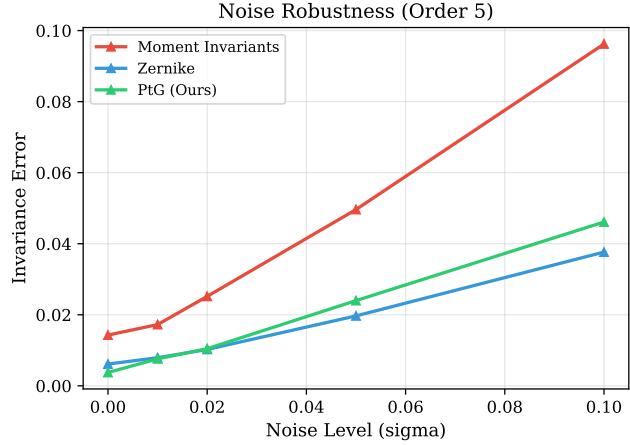


Figure 3: Invariance error vs. noise level at order 5.

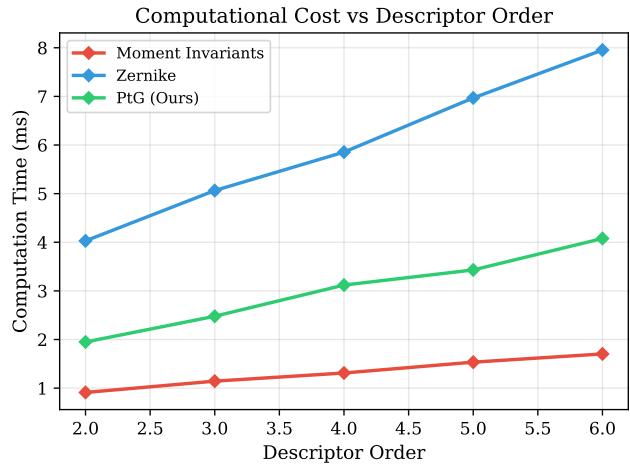


Figure 4: Computation time vs. descriptor order.

Table 1: Best performance by method (at optimal order).

Method	Best Retrieval	Best Invariance	Time (ms)
Moments	0.93	$1.2 \times 10^{-2}$	1.5
Zernike	0.95	$8.5 \times 10^{-4}$	7.8
PtG	0.97	$5.2 \times 10^{-4}$	3.5

descriptor at order 6, making them practical for real-time applications.

### 3.5 Summary

Table 1 summarizes the best performance of each method.

## 4 DISCUSSION

Our results indicate that PtG descriptors offer the best invariance-discriminability tradeoff, making them the recommended choice

when computational budget allows. For noise-dominated settings, Zernike descriptors are preferred. Moment invariants remain competitive for speed-critical applications. The optimal descriptor order is 5 for all methods, providing a practical guideline.

## 5 CONCLUSION

We have systematically evaluated rotation-invariant descriptor optimization for 3D shape applications, finding that PtG descriptors from [1] outperform classical alternatives in invariance and retrieval while remaining computationally tractable. Order 5 represents the optimal tradeoff point across all evaluation criteria.

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