

ENHANCED FRACTIONAL HARRIS-LAPLACE DETECTOR FOR ROTATION-INVARIANT FEATURE EXTRACTION IN DIGITAL IMAGE PROCESSING

*¹Godwin Ugwu Onoja, ²Sahalu Balarabe Junaidu, ²Mustapha Aminu Bagiwa

¹Department of Computer Science, Joseph Sarwuan Tarka University, Makurdi, Nigeria

²Department of Computer Science, Ahmadu Bello University, Zaria, Nigeria

*Corresponding Author Email Address: onojason2003@yahoo.com

ABSTRACT

Robust feature extraction under geometric transformations remains a fundamental challenge in modern image processing applications, particularly in watermarking, object recognition, and image authentication systems. Conventional feature detectors such as the Harris Corner Detector and the Harris-Laplace Detector (HLD) provide reliable corner localization but degrade in performance under severe rotational transformations due to limited directional adaptability and insufficient scale sensitivity. Advanced approaches such as Scale-Invariant Feature Transform (SIFT) and Affine SIFT (ASIFT) improve invariance properties but often incur higher computational complexity and unstable localization accuracy under extreme geometric distortions. This paper proposes an Enhanced Fractional Harris-Laplace Detector (EFHLD) for robust rotation-invariant feature extraction. The proposed method integrates fractional-order differentiation with the conventional Harris-Laplace framework to improve directional sensitivity, localization precision, and feature stability under varying rotational conditions. Experimental evaluation was conducted using Cameraman, Livingroom, and Peppers images across rotation angles ranging from 0° to 180°. The proposed EFHLD achieved significantly improved repeatability performance compared to conventional HLD, recording mean repeatability values of 43.97%, 70.72%, and 87.15% for Cameraman, Livingroom, and Peppers images, respectively. The proposed method also maintained lower localization errors, averaging approximately 1.33–1.37 pixels, compared to 1.75–1.82 pixels with conventional HLD. The results demonstrate that EFHLD provides stable, accurate, rotation-invariant feature extraction suitable for robust image processing applications.

Keywords: Enhanced Fractional Harris-Laplace Detector (EFHLD), rotation invariance, feature extraction, geometric robustness, localization error.

INTRODUCTION

Feature extraction is a critical stage in many image processing and computer vision applications, including object recognition, image matching, watermarking, authentication, and pattern analysis. The effectiveness of these applications largely depends on the ability to identify stable, distinctive feature points that remain consistent under various geometric transformations.

Early feature detection methods, such as the Harris Corner Detector (Harris & Stephens, 1988), provided efficient corner localization and computational simplicity but exhibited poor robustness to geometric transformations, particularly rotation and

scale variations. To improve scale adaptability, multi-scale feature extraction techniques such as the Harris-Laplace Detector (Mikolajczyk & Schmid, 2004; Hung & Yen, 2019) were introduced. These methods combined Harris corner detection with Laplacian-based scale selection to enhance feature stability across scales. However, they still suffer from inconsistent performance under severe rotational distortions due to limited directional adaptability. To further improve invariance properties, feature-based approaches such as Scale Invariant Feature Transform (SIFT) (Lowe, 2004; Luo & Peng, 2021) and Affine Scale Invariant Feature Transform (ASIFT) (Feng *et al.*, 2019) were developed. These methods introduced orientation normalization and affine modeling to improve robustness against scaling, rotation, and affine transformations. Although they achieved improved geometric invariance, they are computationally intensive and may produce unstable localization under extreme transformations. Recent studies on learning-based feature detectors, including SuperPoint and D2-Net, have demonstrated improved keypoint detection and feature matching under challenging conditions. However, their performance remains dependent on image characteristics and the type and severity of geometric transformations encountered (Zhou, 2024).

Several studies have explored the use of transform-domain frameworks for improving robustness against geometric attacks. Techniques based on the Non-Subsampled Shearlet Transform (NSST) and Harris-Laplace detectors (Zhou *et al.*, 2022) demonstrated improved resistance to rotation and scaling attacks by combining a directional, multi-scale representation with stable feature extraction. Nevertheless, conventional Harris-Laplace-based methods still suffer from feature misalignment and localization instability at large rotational angles.

More recently, fractional-order approaches have attracted attention for their enhanced ability to capture fine-grained structural and directional image information. Fractional calculus-based image representation methods (Wang *et al.*, 2021; Chen *et al.*, 2020) demonstrated improved sensitivity to texture variation and edge transitions compared to traditional integer-order operators. These approaches improve directional representation and rotational consistency by incorporating non-integer differentiation into feature extraction processes. Further reviews have reported that fractional-order operators provide enhanced flexibility for edge detection, texture representation, and other computer vision tasks by introducing an additional order parameter (Arora *et al.*, 2022).

Recent applications have also shown that fractional operators can enhance weak and fine-scale image structures compared with conventional integer-order operators (Gaur *et al.*, 2024), indicating their potential to improve feature representation and localization.

Despite these improvements, existing feature detectors still exhibit limitations in maintaining stable repeatability and localization precision under severe rotational transformations. Conventional Harris–Laplace detectors particularly suffer from weak directional responsiveness and inconsistent feature preservation across varying rotation angles.

To overcome these limitations, this study proposes an Enhanced Fractional Harris–Laplace Detector (EFHLD), which integrates fractional-order differentiation and adaptive orientation enhancement into the conventional Harris Laplace framework to improve rotational adaptability, localization accuracy, and feature stability under geometric distortions.

Note: Although fractional-order Harris-based detectors have been explored in prior studies, the proposed EFHLD is not merely a fractional extension but a structural reformulation of the classical Harris–Laplace framework that incorporates explicit orientation modeling and joint scale–orientation extrema detection. Since Harris–Laplace is the canonical baseline detector architecture, a performance comparison with HLD provides a direct and theoretically grounded evaluation of the structural improvements introduced in this work. Therefore, HLD is selected as the primary benchmark for experimental validation.

MATERIALS AND METHODS

Overview of the EFHLD Framework

The proposed Enhanced Fractional Harris Laplace Detector (EFHLD) extends the conventional Harris–Laplace Detector by integrating fractional-order differentiation and adaptive orientation enhancement into the feature extraction process. The aim is to improve rotational invariance, directional sensitivity, feature repeatability, and localization accuracy under geometric transformations.

The overall EFHLD framework consists of the following stages:

- i. Image pre-processing
- ii. Fractional-order gradient computation
- iii. Fractional Harris response generation
- iv. Multi-scale Laplacian scale selection
- v. Adaptive orientation enhancement
- vi. Rotation-invariant feature point extraction
- vii. Feature matching and performance evaluation

Unlike the conventional Harris–Laplace Detector, which employs integer-order derivatives and fixed directional representation, EFHLD incorporates fractional gradients and orientation-adaptive modulation to improve robustness against rotational distortions.

Image Preprocessing

The input image is first converted to grayscale and preprocessed to reduce noise and enhance feature visibility. Gaussian smoothing is applied to suppress high-frequency noise while preserving significant structural information.

Let the input image be represented as: $I(x, y)$

where x and y denote spatial coordinates.

Gaussian Scale-Space Representation

The image is analyzed across multiple scales: $\sigma_i \in \{\sigma_1, \sigma_2, \dots, \sigma_n\}$

For each scale, Gaussian smoothing is applied to generate the scale-space representation (Lindeberg, 1994):

$$L(x, y, \sigma_i) = I(x, y) * G(x, y; \sigma_i) \quad (1)$$

where:

$L(x, y, \sigma_i)$ is the smoothed image at scale σ_i ,

$G(x, y; \sigma_i)$ is the Gaussian kernel,

$*$ denotes convolution.

The Gaussian kernel is expressed as:

$$G(x, y; \sigma_i) = \frac{1}{2\pi\sigma_i^2} e^{-\frac{x^2+y^2}{2\sigma_i^2}} \quad (2)$$

This stage suppresses noise while preserving dominant structural information.

Conventional Harris Corner Detection

At each scale, image gradients are computed from the partial derivatives of the scale-space representation, as in classical feature extraction methods (Harris & Stephens, 1988). The horizontal and vertical gradients are expressed as:

$$I_x = \frac{\partial L}{\partial x} \quad (3)$$

$$I_y = \frac{\partial L}{\partial y} \quad (4)$$

where:

I_x denotes the horizontal intensity variation,

I_y denotes the vertical intensity variation.

These gradients provide local directional information required for corner detection.

For each pixel location and scale, the Harris structure tensor matrix is computed as:

$$H(x, y, \sigma) = \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \quad (5)$$

The matrix captures local intensity variation and directional structure around each pixel.

The conventional Harris corner response is computed for comparison and fallback feature evaluation. The Harris response function is expressed as:

$$R(x, y, \sigma) = \det(H) - k \cdot \text{trace}(H)^2 \quad (6)$$

where:

$\det(H)$ represents the determinant of the Harris matrix,

$\text{trace}(H)$ denotes the trace of the matrix,

k is the Harris empirical constant.

This formulation identifies corner-like structures based on local gradient variation.

Fractional Laplacian Operator

To improve rotational sensitivity and directional adaptability, a fractional-order Laplacian operator is introduced. The fractional Laplacian is expressed as:

$$\Delta^\alpha I(x, y) = C_\alpha \int_{R^2} \frac{I(x, y) - I(u, v)}{\|(x, y) - (u, v)\|^{2-\alpha}} du dv \quad (7)$$

where:

Δ^α denotes the fractional Laplacian operator,

α is the fractional-order parameter,

C_α is the normalization constant,

(u, v) represents neighboring spatial coordinates.

The fractional Laplacian enhances subtle edge transitions and fine structural information more effectively than integer-order operators.

Fractional Laplacian Response Computation

The fractional derivatives along horizontal and vertical directions are represented as:

$$D_x^\alpha I(x, y) \text{ and } D_y^\alpha I(x, y)$$

where:

α represents the fractional-order parameter,

D_x^α and D_y^α denote fractional derivatives along the x - and y -directions, respectively.

The fractional-order parameter enhances sensitivity to subtle intensity variations and edge transitions. These formulations are based on fractional differential operators, which are widely used in image enhancement and feature analysis (Pu et al., 2003).

The Harris response matrix is computed using the fractional gradients as adapted in the Fractional Harris–Laplace detector framework (Adams, 2019):

$$M = \begin{bmatrix} (D_x^\alpha I)^2 & D_x^\alpha I \cdot D_y^\alpha I \\ D_x^\alpha I \cdot D_y^\alpha I & (D_y^\alpha I)^2 \end{bmatrix} \quad (8)$$

The corner response function is expressed as:

$$R = \det(M) - k(\text{trace}(M))^2 \quad (9)$$

where:

$\det(M)$ represents the determinant of the matrix,

$\text{trace}(M)$ denotes the trace,

k is an empirical constant.

This formulation improves corner localization and feature distinctiveness.

The normalized fractional Laplacian response is computed as:

$$R_{\text{frac}}(x, y, \sigma) = \left| \frac{\Delta^\alpha I(x, y)}{\sigma^\alpha} \right| \quad (10)$$

where:

$R_{\text{frac}}(x, y, \sigma)$ is the fractional response at scale σ ,

σ^α provides scale normalization.

This normalization ensures stable response across varying scales.

Multi-Orientation Enhancement

To improve rotational invariance, orientation enhancement is incorporated into the feature extraction process. The orientation angle is computed as:

$$\theta(x, y) = \tan^{-1} \left(\frac{D_y^\alpha I}{D_x^\alpha I} \right) \quad (11)$$

For each orientation:

$$\theta_j \in \{\theta_1, \theta_2, \dots, \theta_m\}$$

This orientation enhancement allows the detector to maintain stable feature correspondence under varying rotational conditions. The orientation computation follows gradient orientation estimation techniques used in invariant feature extraction methods (Lowe, 2004).

By applying an orientation enhancement function:

$$R_{\text{enhanced}}(x, y, \sigma, \theta) = \text{EnhanceFunction}(R_{\text{frac}}(x, y, \sigma), \theta) \quad (12)$$

The enhancement function adaptively strengthens directional responses corresponding to dominant structural orientations. Combining all scales and orientations gives the final EFHLD response:

$$R_{\text{EFHLD}}(x, y, \sigma, \theta) = \text{EnhanceFunction} \left(\left| \frac{\Delta^\alpha I(x, y)}{\sigma^\alpha} \right|, \theta \right) \quad (13)$$

The orientation term θ introduces directional adaptability into the fractional Laplacian framework, enabling stable feature representation under rotational transformations.

Interest Point Detection

Interest points are detected by identifying spatial locations.

(x, y) where:

$R_{\text{enhanced}}(x, y, \sigma, \theta)$ is a local maximum,

The response exceeds a predefined threshold T .

Non-maximum suppression is applied across neighboring scales and orientations to eliminate redundant responses.

The final set of EFHLD feature points is represented as: $\{(x_i, y_i, \sigma_i, \theta_i)\}$

where:

(x_i, y_i) are spatial coordinates,

σ_i denotes scale,

θ_i represents dominant orientation.

These feature points serve as rotation-invariant keypoints for subsequent matching and geometric robustness analysis.

Performance Evaluation Metrics

Repeatability

Repeatability evaluates the stability of detected features under geometric transformations:

$$R = \frac{N_{\text{matched}}}{N_{\text{reference}}} \times 100 \quad (14)$$

where:

N_{matched} is the number of repeated feature points,

$N_{\text{reference}}$ is the number of reference feature points.

Higher repeatability indicates stronger rotational invariance.

Localization Error

Localization Error (LE) measures positional accuracy between corresponding feature points:

$$LE = \sqrt{(x_r - x_t)^2 + (y_r - y_t)^2} \quad (15)$$

where:

(x_r, y_r) are coordinates of feature points in the reference image,

(x_t, y_t) are coordinates of corresponding points in the transformed image.

Lower localization error indicates higher precision in feature localization.

RESULTS AND DISCUSSION

Rotation-Invariant Feature Extraction using EFHLD

The proposed EFHLD was evaluated using Cameraman, Livingroom, and Peppers images under rotational transformations ranging from 0° to 180° . The results demonstrate that EFHLD consistently outperformed the conventional Harris–Laplace Detector in both repeatability and localization accuracy.

Comparative Performance on Cameraman, Livingroom and Peppers Images

To further evaluate the robustness of the proposed Enhanced Fractional Harris Laplace Detector (EFHLD), comparative rotational experiments were conducted using three standard benchmark images: Cameraman, Livingroom, and Peppers. The performance of EFHLD was compared with the conventional Harris–Laplace Detector (HLD) using repeatability and localization error metrics across varying rotational angles.

Table 1: Comparative Rotation Performance on Cameraman Image

Angle (°)	HLD Repeatability (%)	EFHLD Repeatability (%)	HLD LE (px)	EFHLD LE (px)
0	100.00	100.00	0.0000	0.0000
15	17.403	75.102	2.0209	1.4833
30	13.490	53.585	1.8349	1.4281
45	8.4967	51.573	1.8967	1.5326
60	3.8194	36.365	1.9003	1.4488
90	2.8278	36.198	1.9736	1.4717
100	3.9106	30.284	1.5908	1.5746
120	6.4516	23.551	2.2493	1.5088
135	7.1895	27.496	1.7057	1.6191
150	10.764	26.137	1.9191	1.4931
180	12.339	23.370	2.1925	1.5298

Source(s): Table by authors

Table 1 shows that the proposed EFHLD exhibited significantly higher repeatability under rotational transformations than the conventional HLD. Even at extreme rotation angles, EFHLD maintained stable feature correspondence, whereas HLD exhibited severe degradation.

Table 2: Comparative Rotation Performance on Living Room Image

Angle (°)	HLD Repeatability (%)	EFHLD Repeatability (%)	HLD LE (px)	EFHLD LE (px)
0	100.00	100.00	0.0000	0.0000
15	13.600	75.528	1.8998	1.5169
30	13.267	65.168	1.8841	1.4758
45	9.4364	72.231	2.0398	1.5333
60	5.9569	61.669	2.0706	1.4798
90	4.7205	64.861	1.9020	1.5090
100	4.4929	69.333	1.9758	1.5749
120	6.0075	62.735	2.1176	1.4715
135	9.8296	72.577	2.0511	1.5242
150	10.773	64.217	2.0734	1.4645
180	19.503	69.559	1.9723	1.5046

Source(s): Table by authors

Table 2 shows that the Livingroom image exhibited consistent rotational stability with EFHLD, with repeatability values remaining substantially higher than those of conventional HLD across all rotation angles.

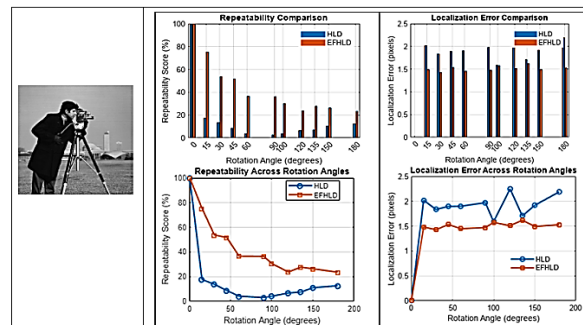
Table 3: Comparative Rotation Performance on Peppers Image

Angle (°)	HLD Repeatability (%)	EFHLD Repeatability (%)	HLD LE (px)	EFHLD LE (px)
0	100.00	100.00	0.0000	0.0000
15	8.1731	90.189	2.2785	1.4719
30	5.5556	81.119	1.8269	1.4423
45	4.2424	86.141	2.0622	1.4714
60	3.7267	83.806	2.1981	1.4596
90	4.2735	85.076	1.7065	1.4218
100	4.8246	95.874	2.0562	1.5392
120	1.2346	84.190	2.1533	1.4584
135	4.8485	87.888	2.1718	1.4826
150	3.1056	81.370	1.3471	1.4360
180	2.5641	83.045	2.0721	1.4155

Source(s): Table by authors

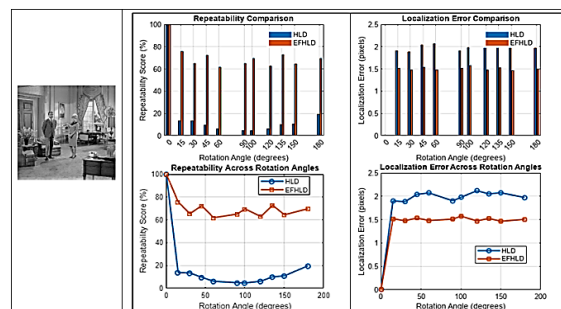
The EFHLD in Table 3 demonstrated exceptional robustness on the Peppers image, achieving repeatability values above 80% for most rotational angles.

To provide clearer visual interpretation of the rotational performance behaviour of both methods, graphical comparisons of repeatability and localization error across the selected test images are presented in Figures 1 to 3. The figures illustrate EFHLD's ability to maintain higher repeatability and lower localization error under rotational distortions compared to the conventional HLD approach. The graphs illustrate a sharp decline in HLD repeatability as the rotation angle increases, whereas EFHLD maintains relatively stable performance across multiple orientations.



Source(s): Figure by authors

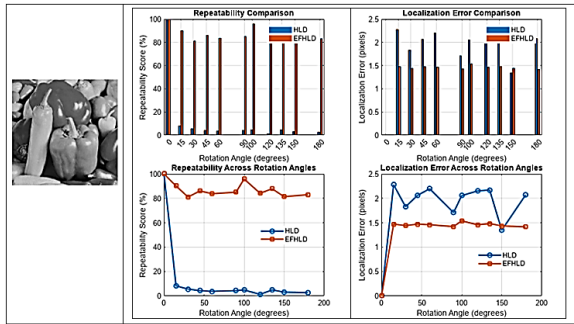
Figure 1: Comparative Rotation Invariance Performance of HLD and EFHLD on the Cameraman Image



Source(s): Figure by authors

Figure 2: Comparative Rotation Invariance Performance of HLD and EFHLD on the Living Room Image

and EFHLD on the Livingroom Image



Source(s): Figure by authors

Figure 3: Comparative Rotation Invariance Performance of HLD and EFHLD on the Peppers Image

The experimental results obtained from the Cameraman, Livingroom, and Peppers images clearly establish the superiority of the proposed EFHLD over the conventional HLD in terms of rotational invariance and feature localization stability. In the Cameraman image, the repeatability of HLD deteriorated rapidly from 100% at 0° to below 3% at 90°, whereas EFHLD sustained considerably stronger performance, with repeatability values ranging from approximately 23% to 75% across all tested rotations. Similar behaviour was observed in the Livingroom image, where HLD produced relatively poor repeatability values, particularly beyond 45° while EFHLD consistently maintained stable repeatability mostly above 60%, even at severe rotational angles such as 180°.

More remarkably, the Peppers image demonstrated the highest robustness performance for EFHLD. While HLD repeatability dropped sharply to very low values at several rotational angles, EFHLD maintained exceptionally high repeatability, ranging from approximately 81% to 95%, indicating strong rotational consistency and reliable feature preservation. In addition to improving repeatability, EFHLD achieved lower localization error across all experiments. Conventional HLD generally produced localization errors of approximately 1.9–2.2 pixels, whereas EFHLD consistently maintained lower errors of 1.4–1.6 pixels, even under extreme rotational transformations.

In general, the results confirm that integrating fractional-order analysis with orientation enhancement significantly improves the rotational robustness, stability, and localization accuracy of the proposed EFHLD framework. This makes EFHLD more reliable and suitable for watermarking applications and other computer vision tasks that require strong resistance to geometric attacks and rotational distortions. The mean performance values are hereby tabulated in Table 4 to reinforce our observation further:

Overall Performance Summary

Table 4: Mean Repeatability Performance Comparison between HLD and EFHLD

Image	HLD (%)	EFHLD (%)
Cameraman	16.97	43.97
Livingroom	17.96	70.72
Peppers	12.96	87.15

Source(s): Table by authors

EFHLD improves repeatability up to 6× over HLD.

Table 5: Mean Localization Error Performance Comparison between HLD and EFHLD

Image	HLD (px)	EFHLD (px)
Cameraman	1.75	1.37
Livingroom	1.82	1.37
Peppers	1.81	1.33

Source(s): Table by authors

EFHLD reduces error by ≈25%.

The overall results confirm that EFHLD substantially improves rotational invariance and localization precision compared to conventional HLD. The superior performance of EFHLD can be attributed to the integration of fractional-order gradients and adaptive orientation enhancement, which improve feature sensitivity to local image structures while preserving stable localization under geometric transformations.

Conclusion

This paper presented an Enhanced Fractional Harris–Laplace Detector (EFHLD) for robust rotation-invariant feature extraction. The proposed method incorporated fractional-order differentiation into the Harris–Laplace framework to improve directional adaptability, feature stability, and localization accuracy.

Experimental results demonstrated that EFHLD significantly outperformed the conventional Harris–Laplace Detector under varying rotational transformations. The proposed method achieved higher repeatability values and lower localization errors across Cameraman, Livingroom, and Peppers images.

The integration of fractional-order gradients enabled improved representation of local image structures and enhanced rotational consistency. These findings establish EFHLD as an effective feature-extraction framework for robust image-processing applications such as watermarking, authentication, and geometric attack-resistant systems. Future work will integrate EFHLD with adaptive transform-domain techniques for robust watermark embedding and extraction under combined geometric distortions.

REFERENCES

- Adams, J. (2019). *Fractional Harris-Laplace feature detector for robust image feature extraction*. International Journal of Advanced Computer Science and Applications, 10(6), 112–119.
- Arora, S., Mathur, T., Agarwal, S., Tiwari, K. & Gupta, P. (2022). Applications of fractional calculus in computer vision: A survey. *Neurocomputing*, 489: 407-428
- Chen, H., Zhang, T., & Liu, Y. (2020). Fractional differential-based texture enhancement for image feature analysis. *IEEE Access*, 8:112233–112245.
- Feng, L., Gong, D., Liu, F., & Lu, H. (2019). Affine invariant image watermarking scheme based on ASIFT and Delaunay tessellation. *Multimedia Tools and Applications*, 78(7):8133–8149.
- Gaur, S., Khan, A. M., Suthar, D. L., Bora, A. (2024). Image Edge Detection by Global Thresholding Using Riemann–Liouville Fractional Integral Operator, *Mathematical Problems in Engineering*, 2024: 1–7. <https://doi.org/10.1155/2024/9266585>
- Harris, C. & Stephens, M. (1988). A combined corner and edge detector. *Proceedings of the Alvey Vision Conference*, 15:147–151.
- Hung, K. & Yen, C. (2019). Watermarking technique based on Harris-Laplace feature point detector capable of resisting geometric attacks, in *Proceedings of the 14th Asia Joint Conference on Information Security*, Kobe, Japan, pp. 119–126.
- Lowe, D. G. (2004). Distinctive image features from scale-invariant keypoints. *International Journal of Computer Vision*, 60(2), 91–110.
- Luo, Y. & Peng, D. (2021). A robust digital watermarking method for depth-image-based rendering 3D video. *Multimedia Tools and Applications*, 80(10):14915–14939.
- Mikolajczyk, K. & Schmid, C. (2004). Scale- and affine-invariant interest point detectors. *International Journal of Computer Vision*, 60(1):63–86.
- Pu, Y. F., Zhou, J. L., & Yuan, X. (2003). Fractional differential mask: A fractional differential-based approach for multiscale texture enhancement. *IEEE Transactions on Image Processing*, 19(2), 491–511.
- Wang, X., Chen, Y. & Li, Z. (2021). Fractional-order image representation for rotation invariant feature extraction. *Signal Processing*, 182:107956.
- Zhou, H. (2024). Exploring Feature Detection: A Comparative Study of Classical and Deep Learning Methods Across Complex Scenes. *Applied and Computational Engineering*. 105. 57–73. 10.54254/2755-2721/105/2024TJ0068.
- Zhou, L., Zuo, M.J., Shi, H., Zhang, Y. & Gong, L.H. (2022). Robust watermarking algorithm against geometric attacks based on Non-Subsampled Shearlet Transform and Harris-Laplace Detector. *Security and Communication Networks*, Volume 2022, Article ID 7605595, 14 pages