Lightweight Adaptive Thresholding for Real-Time 3×3 Go Game Board Recognition Under Dynamic Illumination

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Abstract: Traditional Go stone recognition methods often fail under complex illumination scenarios and are not lightweight enough for an embedded deployment. In order to address this problem, this paper proposes a real-time recognition system for 3×3 Go game boards that integrates dynamic illumination compensation, hybrid edge detection, and multimodal low-dimensional feature fusion. This system employs precomputed lookup tables for Gamma correction, hybrid edge detection based on Sobel gradient fusion and a Canny operator with 3×3 rectangular kernels, and the weighted fusion of wavelet features and compressed LBP descriptors for reducing the computational overhead while maintaining robustness to illumination changes. The experiments carried out on a 900-image dataset across high-intensity illumination, indoor lighting, and low-light conditions achieved an average accuracy of 97% with an inference time of 46 ms, improving the F1 score by 9% in comparison with the conventional methods based on the Otsu algorithm. The ablation studies confirm the contribution of each module of the proposed system, showing an accuracy improvement from 74% to 97% under low-light conditions. The proposed framework balances accuracy and efficiency, demonstrating a strong potential for embedded Go robots and broader lightweight recognition applications (edge computing devices) in dynamic environments.

Keywords: Go game board recognition, Adaptive threshold segmentation, Hybrid edge detection, Multimodal feature fusion, Lightweight feature extraction.

1. Introduction

Go recognition serves as a critical component in intelligent gaming systems, where accuracy directly determines user experience in human-computer interactions. The proliferation of embedded devices has intensified the demand for real-time analysis systems across competitive training and online gaming scenarios. However, conventional methods relying on fixed threshold segmentation and manual feature extraction exhibit segmentation errors under complex illumination while struggling with computational efficiency for embedded platforms. The existing approaches like Hough transform-based board detection demonstrate an insufficient robustness in dynamic lighting (Huang & Liu, 2021), and Harris operator-driven feature extraction proves susceptible to specular reflection interference (Feng et al., 2019). This creates an unresolved challenge: achieving an accuracy-efficiency balance under computational constraints for embedded Go recognition systems.

The current research confronts four fundamental conflicts: (1) Illumination sensitivity in traditional threshold segmentation elevates the false detection rates in shadow/highlight regions (Safonov et al., 2018); (2) Complex edge detection and high-dimensional feature extraction impose prohibitive computational loads which are incompatible with low-latency requirements (Zhang et al., 2025); (3) Direct application of lightweight models to Go game scenarios can lead to overfitting due to stone feature homogeneity, and Hessian-based corner detection fails in distorted edge regions, while neural network-based methods show a limited generalization with low-resolution inputs (Chen et al., 2023); (4) Although CNN-based (Anuradha et al., 2024) solutions improve recognition accuracy, their high computational complexity hinders the real-time embedded deployment of edge computing devices.

Recent advances focus on robustness to illumination changes and computational optimization. In image enhancement, MLP-based correction methods enhance feature extraction through bilateral filtering (Li et al., 2024) but suffer from discontinuous edges due to fixed threshold dependencies. Although the Canny operator is one of the common edge detection methods among the traditional image processing methods, it is susceptible to noise and a limited detail capturing ability during edge detection under strong lighting changes (Deng et al., 2013). Improved adaptive Canny-based

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algorithms integrating optimal thresholding and Otsu's method offer computational efficiency insights. Nevertheless, a systematic optimization of lightweight feature fusion with real-time performance remains unaddressed.

This study proposes a lightweight embedded adaptive automatic visual recognition system for 3×3 Go game board recognition through algorithmic optimization, addressing the traditional methods' performance limitations in dynamic environments.

The theoretical framework of this study is constructed upon four key components: (1) The integration of CLAHE and Gamma correction to take into account both local contrast enhancement and global brightness correction for improving image quality and processing efficiency; (2) The 3×3 Sobel gradient and adaptive Canny algorithm are fused to achieve an accurate edge detection for the Go board; (3) The multiple features of Wavelet Features, LBP Texture Features and Morphological Features are dynamically adjusted by the adaptive weighting mechanism to enhance the robustness to illumination changes and achieve an effective feature extraction; (4) Classifying by using a linear classifier to obtain the distribution of each stone on the Go board. The experimental results show that the F1 score is improved by 9% in comparison with the baseline method for the multi-illumination data set containing 900 images, and the ablation study further confirms the contribution of each module. During the actual deployment, the system achieves a reasoning latency of 46 milliseconds and an overall accuracy of 97% on the NVIDIA Jetson Nano platform.

The remainder of this paper is structured as follows. Section 2 reviews the theoretical foundations and evolution of adaptive thresholding techniques, with a particular emphasis on the proposed 3×3 Go game board recognition system and its Greatest-Of adaptive threshold method, and surveys the recent advances in improved adaptive thresholding across diverse application domains. Section 3 describes the proposed methodology, specifies its theoretical rationale, and presents a detailed implementation workflow. Further on, Section 4 provides a comprehensive experimental evaluation that validates the effectiveness of the proposed approach. Finally, Section 5 concludes this paper, summarizes its key findings, and outlines certain directions for future research.

2. Literature Review

2.1 Introduction to Adaptive Thresholding

Adaptive thresholding represents a significant advancement over conventional static thresholding methods, which are becoming increasingly inadequate for dealing with complex, dynamic systems and data. Static thresholds cannot effectively respond to varying conditions, making them unsuitable for dynamic workloads in cloud systems, anomaly detection, and other applications with fluctuating conditions. This limitation has spurred an increasing research interest in adaptive thresholds that can minimize model uncertainty in detection systems.

The core principle of adaptive thresholding involves evaluating deviations in the monitored parameters and adjusting thresholds accordingly. Adaptive methods have been applied in various domains, such as in dynamic job shop scheduling (DJSS) to optimize the scheduling strategies in order to reduce latency and energy consumption (Han & Yang, 2021). By applying the mixed strategy of "multi-feature extraction, adaptive weight fusion, and structured knowledge", they are used for solving problems such as insufficient feature utilization and blurred boundaries, and achieving high-precision entity recognition (Gao, 2024). In addition, a framework combining Retinex and dual-channel priors is proposed for addressing the problems common in low-light image enhancement, such as halo, overexposure, loss of edge detail, and noise amplification (Chen & Li, 2024).

In video processing, adaptive thresholds are particularly valuable as videos represent complex, high-dimensional signals with frequently changing spatio-temporal properties. Dynamic thresholds have been developed for various video applications including scene change detection, crowd anomaly detection, and fall detection systems. For instance, dynamic thresholds based on optical flow can adapt to changing light conditions in crowd monitoring without requiring prior knowledge or extensive training (Liu et al., 2014). Similarly, vision-based fall detection systems use dynamic thresholds based on local statistical attributes to improve accuracy (Otanasap & Boonbrahm, 2017).

Despite the advantages of adaptive thresholding methods, they can be affected by high computational complexity due to the large amounts of data they must process. This challenge necessitates ongoing research for developing more efficient algorithms and implementation strategies that can maintain performance while reducing the computational requirements - such as low CPU utilization and low memory usage.

2.2 The Proposed 3×3 Go Game Board Recognition System and Greatest-Of Adaptive Threshold Method

The proposed 3×3 Go game board recognition system represents an important advancement in adaptive thresholding methodology, particularly through its implementation of the Greatest-Of (GO) approach. This system calculates adaptive thresholds by examining multiple detection windows and selecting the maximum values from each window for comparison against a minimum noise level. As Ens et al. (2015) explain, this modified Constant False Alarm Rate (CFAR) algorithm "takes two windows, one before the point and one after the threshold point. Then, the greatest value is taken in each window (greatest of, GO) and is compared with the minimum noise level". This approach contrasts with static thresholding techniques that set fixed detection boundaries and cannot adapt to changing signal conditions.

In practical implementations, the GO approach demonstrates its utility in various detection systems. For example, in energy detection systems, this concept manifests as selecting "the highest of the three" energy values from multiple detectors before determining the threshold parameters (Thenmozhi, 2015). This selection process enables a more accurate threshold determination based on the strongest available signal.

More sophisticated implementations of adaptive thresholding have expanded on these concepts by creating multiple adaptive thresholds that subdivide the regions of uncertainty. Mahendru et al. (2021) describe a novel approach that utilizes "two adaptive/dynamic thresholds" to further classify signal detection in uncertain zones. These thresholds are considered "adaptive" because "they depend on the variable uncertain noise (ρ) and a dynamically changing parameter (ρ′)," allowing the system to shrink the boundaries of uncertainty and improve detection probability even at low signal-to-noise ratios (Mahendru et al., 2021).

Beyond signal processing, adaptive thresholding methods have been applied to image binarization through techniques like the "two-dimensional maximum entropy adaptive threshold selection method". This approach addresses challenges with weak targets or strong noise interference by correlating "a membership function parameter... with a threshold value" and finding "the maximum value of the fuzzy partition entropy" as the segmentation threshold (Indriyani et al., 2021). The method utilizes "the spatial relationship between the image pixels" to improve noise immunity in comparison with one-dimensional methods that only consider pixel gray information (Chen et al., 2018).

2.3 Applications of Improved Adaptive Thresholding Methods

Adaptive threshold techniques have been implemented across diverse fields with n otable success.

For example, in the field of signal and image processing, some researchers have proposed an improved adaptive thresholding function to overcome the shortcomings of the traditional wavelet transform threshold denoising method. In comparison with the traditional hard and soft thresholding functions, the proposed function performs better in terms of mean square error and peak signal-to-noise ratio. Furthermore, by introducing the improved Drosophila optimization algorithm and replacing the uniform distribution with the normal distribution, the local extremum and the iteration rate are effectively balanced, thus optimizing the overall process of wavelet threshold denoising (Donoho & Johnstone, 1995).

In the field of image segmentation, the development of multi-level thresholding technology has promoted the progress of image saliency detection. For example, the Saliency Cuts method improves the accuracy of object detection by improving the Otsu algorithm to achieve a three-level threshold division and dividing the image into four regions (Mukhiddinov et al., 2020).

In the field of wireless communication and sensing, the adaptive threshold detection algorithm based on image binarization technology is introduced into spectrum sensing, and the system can perform dynamic self-training based on historical statistical data, and its performance is improved by up to 30% in comparison with the traditional energy detector in an environment with a low signal-to-noise ratio (Muralidharan et al., 2015). In addition, the threshold adjustment method based on particle swarm optimization has been studied to achieve an effective trade-off between high and low thresholds, so as to suppress interference and overcome the problems of fixed thresholds and threshold drift (Sun, 2023).

In environmental monitoring, the adaptive threshold mechanism can dynamically adjust the threshold according to the change of environmental conditions, so as to improve the robustness of indoor and outdoor light intensity classification (Ghedia & Vithalani, 2021).

While the current adaptive methods and Go-related research have achieved a certain progress, the following research gaps persist:

Lightweight design-Accuracy Trade-off

The existing approaches reduce the computational costs through low-dimensional feature fusion, but compressed LBP descriptors may sacrifice high-frequency texture information. This necessitates the exploration of more efficient feature reduction strategies.

Dynamic Scenario Generalization

The current algorithms predominantly focus on other application scenarios, lacking validation in 3×3 Go game boards recognition or real-time embedded deployment.

This study addresses high-precision Go recognition under dynamic illumination through an algorithm-level lightweight design, providing a viable solution for embedded real-time systems. Future research should prioritize cross-scenario generalization, dynamic feature weight optimization, and hardware-level acceleration strategies in order to advance the practical applications of Go robots.

3. Methods

3.1 Dynamic Illumination Compensation

3.1.1 CLAHE Enhancement

Before applying illumination compensation, the raw image captured by the camera in RGB format is first converted to a grayscale image. This preprocessing step is essential for reducing the computational complexity of the subsequent algorithms by reducing the data dimensionality from three channels to one. The conversion utilizes the standard luminosity method, which aligns with the human visual perception of brightness. This grayscale image serves as the unified input for the CLAHE enhancement and Gamma correction modules. In order to alleviate the problem of uneven illumination, the input image is divided into 3×3 sub-regions by using the adaptive histogram equalization technology of limiting contrast, and the histogram threshold truncation is implemented on each sub-region (the contrast is limited to C). The mapping function is defined as:

$$\mathrm{T}(\mathrm{r}_k, \mathrm{k}) = \sum_{i=0}^{k} \frac{n_i^{'}}{N^{'}}, k = 0, 1, ..., L = 1 \tag{1}$$

where $n_i^{'}$ represents the gray level intensity of the pixel in the k-th sub-region; k denotes the index of the sub-region ranging from 0 to L-1, L is the total number of sub-regions; $n^{'}$ represents the height of the modified histogram interval obtained after threshold truncation and redistribution on the i-th gray level, and $N^{'}$ represents the total number of effective pixels for histogram equalization calculation in the subregion after truncation and redistribution. By calculating the normalized cumulative distribution of the truncated histogram, the mapping function establishes the gray transformation relationship for each sub-region.

3.1.2 Adaptive Gamma Correction

Gamma correction is implemented by using discretized Gamma values within the range of [0.5, 2.0]. These values are used for generating precomputed lookup tables (LUTs) for intensity transformation, allowing for adaptive brightness enhancement based on the image's luminance characteristics:

$$I_{(\mathrm{x,y})} = 255(\frac{i_{(\mathrm{x,y})}}{255})^{\Upsilon}, \Upsilon \sim \mathrm{U}(0.5, 2.0) \tag{2}$$

The correction parameter Υ follows a uniform distribution, in the context of which precomputed LUTs are employed to accelerate the real-time computation. When processing the input image, the correction of each pixel requires only one memory access operation, which greatly minimizes the computational delay and speeds up the processing speed.

3.2 Hybrid Edge Detection

3.2.1 Sobel Gradient Fusion

The input image is processed through illumination compensation to improve the visual clarity and details of the picture, and then the horizontal and vertical gradients (G_x,G_y) are calculated by using a 3×3 convolution kernel to obtain an edge intensity map:

$$G_x = \begin{pmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{pmatrix}, G_y = G_x^T \tag{3}$$

$$G = \sqrt{G_x^2 + b_y^2} \tag{4}$$

3.2.2 Adaptive Canny Edge Detection

The Canny algorithm thresholds are dynamically configured based on the median grayscale value M of the image. Weak edges connected to strong edges (>T(high)) are preserved through hysteresis thresholding:

$$T_{high} = 1.5M, \quad T_{low} = 0.75M \tag{5}$$

3.2.3 Laplacian of Gaussian (LoG) Filter-based Enhancement

Detail enhancement is achieved using a LoG filter with σ=1.5. Binarization is performed by using Otsu's algorithm to maximize inter-class variance, where ω_0 and ω_1 represent the class probabilities, with μ_0 and μ_1 denoting their respective means:

$$\nabla^2 G(\mathrm{x}, \mathrm{y}) = \frac{x^2 + y^2 - 2\delta^2}{\delta^4} \bullet e^{-\frac{x^2+y^2}{2\delta^2}} \tag{6}$$

$$\delta_b^2(\mathrm{T}) = \omega_0(\mathrm{T})\omega_1(\mathrm{T})[\varphi_0(\mathrm{T}) - \varphi_1(\mathrm{T})]^2 \tag{7}$$

Through the fusion of the Sobel gradient, Canny algorithm and Laplacian of Gaussian filter, the edges in the image can be accurately extracted, which provides the basis for the subsequent independent analysis of each Go board square.

3.3 Morphological Post-processing

Morphological post-processing is performed on the obtained edge map features by first performing an opening operation using a 3×3 rectangular kernel for Noise Removal to eliminate the isolated noise caused by image acquisition noise, and then performing a morphological closing operation using a 5×5 elliptical kernel for Hole Filling. This process smoothens the stone contours, allowing for the accurate positioning of the black and white Go stones. The specific formula is as follows:

$$A \bullet \mathrm{B} = (\mathrm{A} \ominus \mathrm{B}) \oplus \mathrm{B} \tag{8}$$

$$A \bullet C = (\mathrm{A} \oplus C) \ominus C \tag{9}$$

where A is the input image, B is a 3×3 rectangular kernel, C is a 5×5 elliptical kernel, and ⊖ and ⊕ represent the erosion and dilation operations, respectively.

The algorithmic workflow incorporating these improvements is illustrated in Figure 1.

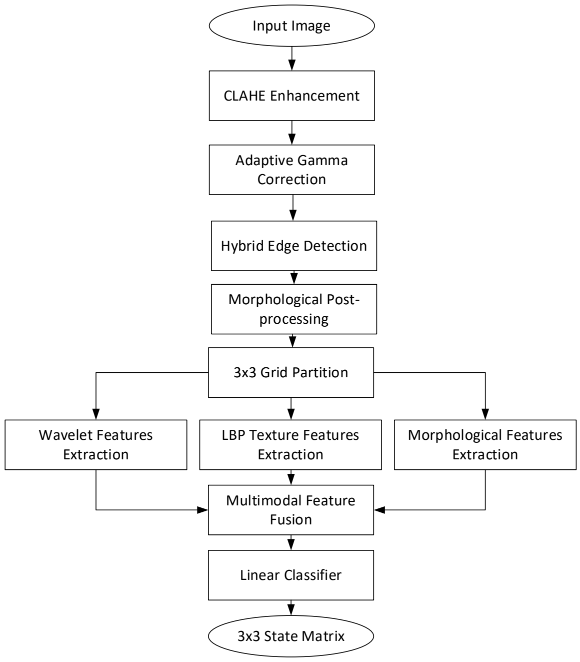

Figure 1. Flowchart of the improved algorithm implementation

3.4 Multimodal Feature Fusion

3.4.1 Wavelet Features

A two-level Haar wavelet decomposition is applied to the binary edge map obtained from the hybrid edge detection stage. Then, the mean (μ) and variance (σ²) are extracted from high-frequency subbands (LH_2, HL_2, HH_2) to construct a 6-dimensional feature vector, thereby effectively describing the local frequency domain characteristics of the image:

$$F_{wavelet} = [\mu_{LH}, \sigma_{LH}^2, \mu_{\mathrm{LH}}, \sigma_{LH}^2, \mu_{\mathrm{LH}}, \sigma_{LH}^2] \tag{10}$$

3.4.2 LBP Texture Features

In the LBP feature extraction step, the texture information is obtained by calculating the gray relationship between each pixel and its neighboring pixels. Specifically, for each pixel in the image, a circular or square neighborhood of a fixed size is selected with that pixel at the center. The grayscale value of the central pixel is used as a threshold, and a point-by-point comparison is made with the grayscale values of each pixel within the neighborhood. If a neighboring pixel's value is greater than or equal to the central pixel's value, it is marked as 1; otherwise it is marked as 0. By arranging these binary bits in a predefined sequence, a binary code representing the local texture pattern at that center point is obtained. Converting this code to a decimal integer yields the LBP value for that position. After traversing all the pixel positions in the entire image, a LBP response map is generated that is exactly the same size as the original image. For an 8-neighborhood pixel region around the center pixel, the LBP feature is represented by an 8-bit integer value encoded in the form:

$$L_{LBP} = \sum_{p=1}^{7} s(g_p - g_c) \bullet 2^p \tag{11}$$

$$s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & others \end{cases} \tag{12}$$

3.4.3 Morphological Features

In the morphological analysis step, the position of each stone is determined through the contour analysis. The shape compactness is quantified by independently calculating the perimeter-area ratio (C is the perimeter of the contour and S is the area of the contour), and together with the seven Hu invariant moments, an eight-dimensional morphological feature vector is constructed, which is integrated by weighting in the subsequent feature fusion stage, and provides a discriminative shape description for a classifier to distinguish black and white Go stones and blank areas:

$$R = \frac{C}{S} \tag{13}$$

$$F_{\text{morph}} = [R, \Phi_1, \Phi_2, ..., \Phi_7] \tag{14}$$

3.4.4 Feature Fusion

Wavelet features, LBP descriptors, morphological features and Hu moments are integrated into a unified high-dimensional feature vector (hereinafter referred to as edge map features) through weighted fusion (the adaptive allocation of weight sum to 1), and more discriminative joint features are found based on the complementarity between different features:

$$F = [\alpha F_{wavelet}, \beta F_{LBP}, \gamma R, \delta\phi_1, \ldots, \delta\phi_7] \tag{15}$$

In equation (15), α, β, γ, and δ are learnable weight coefficients, not fixed scalars. They are initialized randomly and optimized jointly with the linear classifier weights via Gradient Descent during the training phase. The optimization objective is to minimize the classification loss (e.g. Cross-Entropy loss), allowing the model to adaptively assign higher weights to the feature components that contribute most effectively to distinguishing stones from the background under varying illumination conditions.

4. Experiment and Results

4.1 Experimental Settings and Data

A camera with a fixed focal length of 50mm was positioned perpendicular to a physical 45cm×45cm Go board for image acquisition. Diverse lighting conditions were simulated using a programmable illumination control system, specifically including:

1. High-intensity illumination (1,000–3,500 lux): A broad-spectrum lamp mounted 1.2 m above the board simulated intense lighting with cast shadows;
2. Indoor lighting (300–1,000 lux): Multi-angle diffuse lighting replicated uneven indoor illumination;
3. Low-light conditions (10–300 lux): Ambient lighting only, with the primary light sources disabled.

Under each lighting scenario, 300 raw images were captured, totalling 900 RGB images. To simulate camera sensor variations, random ISO and shutter speed adjustments were introduced during image acquisition. All images were subsequently downsampled to 600×600 pixels.

For annotation purposes, the semi-automatic labeling tool LabelGo v2.3 generated corresponding .npy files storing 3×3 board coordinate matrices (1: black stone, -1: white stone, 0: empty intersection). Manual verification was conducted by three annotators to ensure labeling consistency and accuracy. The dataset was divided into training (630 images), validation (180 images), and test sets (90 images) in a 7:2:1 ratio. The overall process corresponds to the workflow illustrated in Figure 1.

During training, the model's output is compared with the actual results. By continuously optimizing the learnable parameters and weights within the model, the difference between the two is minimized, thereby training the model. The training set is used for model training to optimize the learnable parameters (α, β, γ, δ) in the model and the weights of the linear classifier. The validation set is used for model evaluation to guide the training direction by monitoring the overfitting phenomenon and providing feedback for hyperparameter adjustment. The test set is used for finally evaluating the generalization ability of the trained model and testing its recognition robustness for unknown samples. The test set includes images under different lighting conditions. By testing the images, it can be verified whether the adaptive threshold is effective. All the images in this experiment are from the test set.

The whole recognition process is as follows: the 600x600 pixel Go board image is preprocessed. Firstly, the uneven illumination is compensated by CLAHE, and the overall contrast of the image is enhanced by Adaptive Gamma Correction, which lays the foundation for subsequent processing. Then the Hybrid Edge Detection strategy is employed to extract the initial edge by combining the Sobel operator and Canny algorithm, and then the Laplacian of Gaussian filter is used for enhancing the details to obtain the binary edge image. After obtaining the binary edge image, morphological post-processing is applied using a 3×3 rectangular kernel for opening and a 5×5 elliptical kernel for closing to smooth the contours and eliminate noise. Subsequently, the image is divided into 3×3 sub-regions. From these refined regions, three types of features — namely, 6-dimensional Haar wavelet statistical features, local binary pattern (LBP) texture histograms, and 8-dimensional morphological features (including C/S and Hu moments) — are extracted and fused into a unified feature vector. Finally, a linear classifier is applied to each 3×3 sub-region to recognize the stones, and a 3×3 matrix is output, wherein 1 represents a black stone, -1 represents a white stone, and 0 represents an empty intersection, thus completing the recognition of the stones on the entire Go board. Figure 3 displays the visualized recognition results, demonstrating the accurate detection of black and white stones.

4.2 Experimental Results

In relation to actual Go game scenarios, since the stones are placed on the crossline, using a 3×3 board in this paper will result in extra edges, which will have a negative impact on their recognition . Therefore, this paper simulates the actual placement of Go stones by truncating and scaling a complete Go board and placing Go stones on the 3×3 board, while reducing the interference of unnecessary lines.

High-intensity Illumination (1,000–3,500lux):

Elevated light intensity and specular reflections from white stones increased the recognition complexity. Repeated experimental trials demonstrated a 97% average stone recognition rate. Figure 2 shows the original image, while Figure 3 illustrates the recognition output after high-intensity illumination processing. This image demonstrates that it can be processed and recognized normally even under high-intensity conditions.

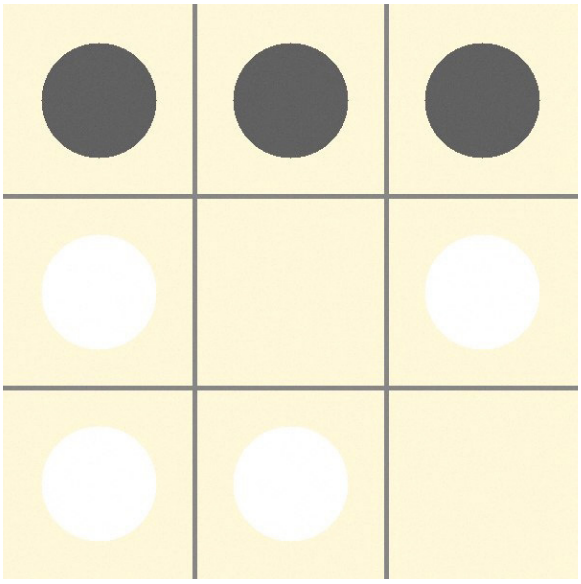

Figure 2. Original image with high-intensity illumination

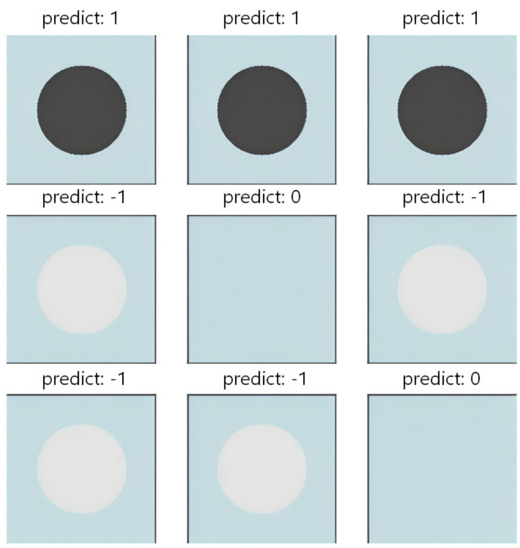

Figure 3. Image after high-intensity illumination processing

Indoor Lighting (300–1,000 lux):

In contrast to high-intensity illumination scenarios, diffuse surface reflections and simulated pixel blurring introduced illumination heterogeneity. The recognition accuracy reached 98% across repeated trials under this condition. Figures 4 (original image) and 5 (detection results after illumination processing) illustrate the system performance.

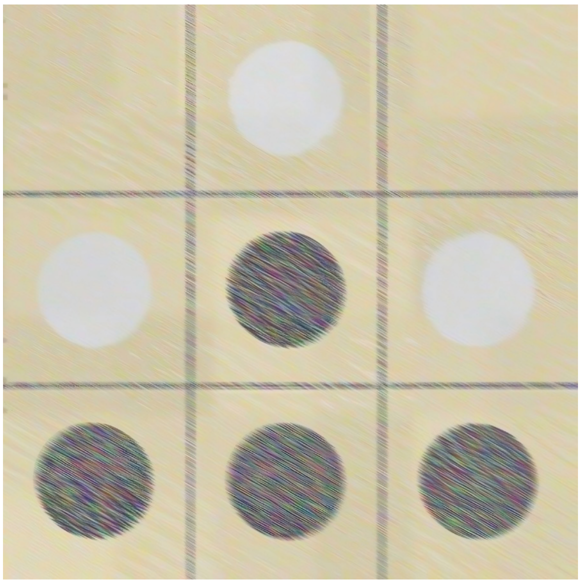

Figure 4. Original image with indoor lighting

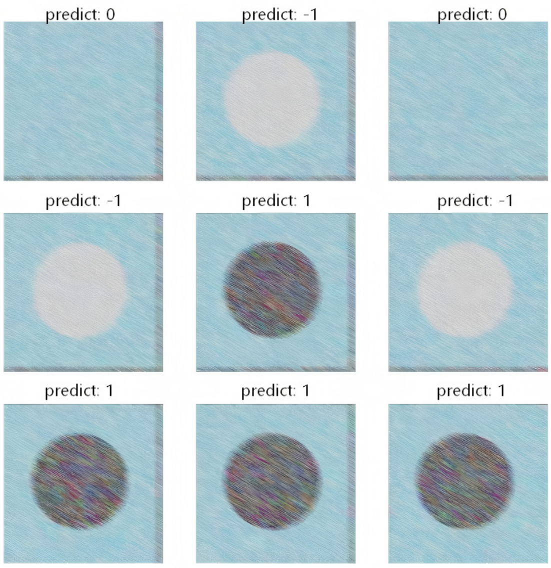

Figure 5. Image after indoor lighting processing

Low-light Conditions (10–300 lux):

Significantly pronounced shadows around the Go stones and a diminished grayscale discriminability of white stones posed recognition challenges. The experimental results confirmed a ≥97% recognition accuracy in dim environments, as shown in Figures 6 (original image) and 7 (detection output after illumination processing).

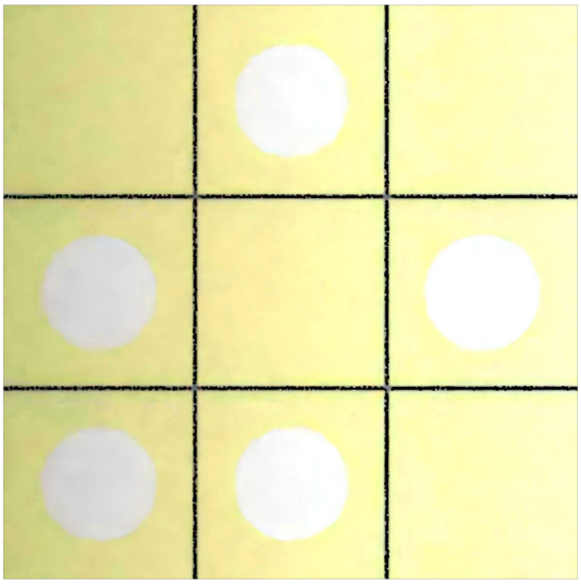

Figure 6. Original image under low-light conditions

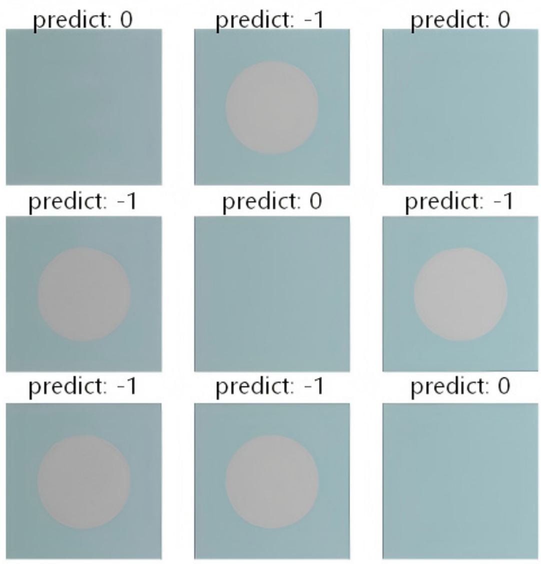

Figure 7. Image after low-light processing

Batch testing across all illumination conditions yielded the performance metrics summarized in Table 1.

Table 1. Algorithm performance metrics under varying illumination conditions

Lighting conditions	Accuracy (%)	Recall (%)	F1 Score (%)	Sample size
Strong light	97	96	97	300
Indoor light	98	97	97	300
Low light	96	95	96	300

The experimental data shows that the system achieves a 97%, 98% and ≥ 97% recognition accuracy in a strong light (1,000-3,500 Lux), indoor light (300-1,000 Lux) and low-light (10-300 Lux) environment, respectively. The stability performance at different illumination levels (an accuracy fluctuation < 3%) directly verifies the effectiveness of self-adaptation, which enables the system to automatically sense the change of ambient brightness and adjust the preprocessing parameters in real time. The Dynamic Illumination Compensation automatically optimizes the threshold by analyzing the gradient distribution for the image: a more stringent combination of thresholds is used for suppressing false edges under strong reflection conditions, and the threshold is relaxed to retain the effective contour under low-light conditions. This adaptive mechanism ensures that Hybrid Edge Detection can maintain a complete Go board structure extraction under various lighting conditions.

4.3 Comparative Experiments and Ablation Analysis

To validate the effectiveness of the proposed method, the baseline method employs Otsu adaptive threshold segmentation combined with 3×3 rectangular kernel-based morphological closing operations. The comparative results are summarized in Table 2 below:

Table 2. Performance comparison for the benchmark method and the proposed method

Method	Accuracy (%)	Recall (%)	F1 Score	Inference time (ms)
Benchmark method	89	87	88	42
The proposed method	97	96	95	46

As shown in Table 2, the improved model consistently outperforms the baseline model with regard to accuracy. While exhibiting a marginally higher inference time (a 4ms increase), the significant 9% improvement in accuracy justifies this trade-off for real-time applications. These results further confirm the efficacy of multimodal feature fusion.

Ablation experiments were conducted to assess the contribution of individual components in the proposed adaptive algorithm for 3×3 Go game board recognition. Four configurations were evaluated:

- Model A: Dynamic illumination compensation only;
- Model B: Model A + hybrid edge detection;
- Model C: Model B + multimodal feature fusion;
- Model D: Full proposed model.

Testing under high-intensity illumination, indoor lighting, and low-light conditions yielded the results in Table 3.

The ablation analysis (Table 3) reveals progressive accuracy improvements: Model A (dynamic compensation) → Model B (+hybrid edges) → Model C (+multimodal fusion), culminating in Model D's 97% accuracy. This demonstrates the synergistic optimization of the critical components:

Table 3. Ablation study results

Model	Lighting conditions	Accuracy (%)	Recall (%)	F1 Score (%)
A	Strong light	80	78	79
A	Indoor light	82	80	81
A	Low light	75	73	74
B	Strong light	88	86	87
B	Indoor light	90	88	89
B	Low light	83	81	82
C	Strong light	93	92	92
C	Indoor light	94	93	93
C	Low light	88	86	87
D	Strong light	97	96	97
D	Indoor light	97	97	97
D	Low light	96	95	96

1. Dynamic illumination compensation mitigates uneven lighting effects;
2. Hybrid edge detection (Sobel gradient fusion + adaptive Canny algorithm) preserves structural integrity;
3. Multimodal feature fusion enables a comprehensive Go stone characterization;
4. Intelligent morphological processing eliminates noise while maintaining topological accuracy.

The results confirm the algorithm's robustness across diverse illumination conditions, achieving a <3% accuracy variance between different lighting scenarios. This component-wise analysis substantiates the necessity of an integrated optimization for the practical embedded deployment of the proposed algorithm.

5. Discussion and Conclusion

This study addressed the challenge of accurate Go stone recognition on a 3×3 board under complex illumination by integrating dynamic illumination compensation, hybrid edge detection, and multimodal feature fusion into a lightweight adaptive framework. Evaluated on a 900-image dataset across strong light (1,000–3,500 lux), indoor light (300–1,000 lux), and low-light (10–300 lux) scenarios, the proposed system achieved an average accuracy of 97% with an inference time of only 46 ms. In comparison with the conventional Otsu-based methods, this represents a 9% improvement in the F1 score while maintaining a real-time performance suitable for the embedded deployment of the proposed system.

The results demonstrate several key contributions. First, adaptive Gamma correction and CLAHE-based compensation proved effective in mitigating specular reflections and shadow artifacts. Second, the hybrid edge detection strategy - combining Sobel gradient fusion and adaptive Canny operators - improved structural integrity under variable illumination conditions. Third, multimodal low-dimensional feature fusion, integrating wavelet coefficients, compressed LBP descriptors, and morphological features, provided discriminative power while avoiding high-dimensional bottlenecks. The ablation studies validated the modular design: the accuracy improved progressively from 74% with dynamic compensation alone to 96–97% when all modules were combined, highlighting the importance of feature fusion and morphological optimization.

Beyond the empirical results, this paper represents a methodological contribution with regard to low resource consumption in informatics and control applications. The precomputed Gamma LUTs reduced computational complexity by 60%, while the compact 3×3 kernels accelerated edge detection without reducing accuracy, demonstrating how carefully designed low-complexity modules can balance robustness and efficiency. Thus, the proposed system provides both a practical solution for Go robots and a transferable framework for lightweight adaptive thresholding under dynamic conditions in other domains such as embedded vision, robotics, and intelligent monitoring.

Future research will focus on extending this approach to larger Go boards and more complex configurations, exploring hardware-level acceleration strategies, and generalizing adaptive thresholding techniques to other real-time recognition tasks. By integrating algorithmic efficiency with illumination robustness, this study advances the design of embedded recognition systems that meet the dual requirement of accuracy and real-time performance.

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