Intelligent Scissors
Image Processing Tool

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June 24, 2026

Contents

1 Project Structure

The intelligent scissors image processing tool is composed of three primary modules:

- **User Interface:** Includes image upload window, operation panel with interactive path control (left-click to start, dynamic preview, click to confirm), coordinate display, and control buttons.
- **Image Algorithm Module:** Color images undergo grayscale conversion and gradient-based preprocessing; Dijkstra's algorithm is used for path search. Black-and-white images combine gradient, Laplacian zero-crossing, and direction consistency, with seed point injection for path optimization.
- **Image Operation Module:** Supports export in PNG and JPEG formats, automatic path closure detection, and manual editing.

2 Code Design

2.1 Project Framework

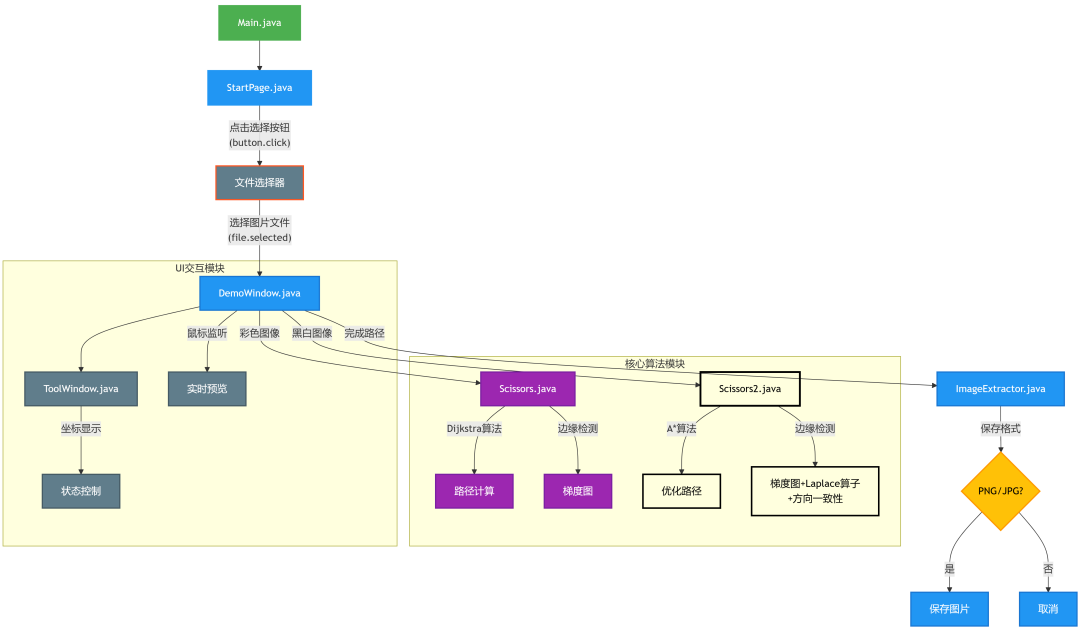

Figure 1: project framework

2.2 Data Structures

Structure	Description
Array	`float[][] gradsMap` – Gradient map for edge strength
List	`List<Point>` – Stores confirmed path points
Priority Queue	`PriorityQueue<Node>` – Expands path nodes by cost
Map	`Map<Point, Integer>` – Point stability tracking
Custom Class	`Node` – Stores coordinates, cost, and parent
BufferedImage	`BufferedImage pathOverlay` – Real-time path rendering
Set	`Set<Point>` – Ensures uniqueness in cooling points

2.3 Interaction Optimization

- Resolution adaptation and UI centering
- Path color preview: blue for preview, red for confirmed
- Mini-toolbar with coordinates and controls
- PNG and JPEG format support
- Executable packaging with embedded JRE

3 How to Use

3.1 Uploading an Image

Click the **Upload Image** button to select the image you want to process.

3.2 Main Interface Operations

In the main interface, the following operations are available:

a) Left-click to set the starting point of the path;

b) Move the mouse to preview the dynamic path;

c) Click again to confirm the end point of the path;

d) Press `Enter` to perform image segmentation.

3.3 Supported Features

a) Real-time path calculation;

b) Manual path adjustment;

c) Export of the segmented image;

d) `Ctrl+Z` to undo the last seed point (including both cooling points and manual anchors);

e) Automatic segmentation when the path is nearly closed.

4 Image Processing

The program reads the original image from the user-specified path and obtains its dimensions. It then calculates the scaling ratio based on a target maximum width and height, taking the smaller of the width and height ratios to preserve the aspect ratio, thereby generating the dimensions for the scaled image. Bicubic interpolation is used to improve rendering quality, and the scaled image is returned.

To enhance performance, grayscale and color images are processed separately. By performing type checking, dynamic pixel sampling, and tolerance comparison, the program determines whether an image is grayscale (if the differences between R, G, and B are all less than 10, it is considered grayscale) and selects different pathfinding algorithms accordingly.

4.1 Color Images

For color images, the input image is first converted to grayscale. Through debugging, it was found that using the average value of RGB components to generate a luminance map provides good practical performance. The Sobel operator implementation follows standard computer vision practices (1). A simplified Sobel operator is used to compute the horizontal and vertical gradients, denoted as I_x and I_y, respectively. The gradient magnitude image is then synthesized as follows:

$$G = \sqrt{I_x^2 + I_y^2}$$

This gradient magnitude image indicates edge strength. The gradient magnitude is mapped to a static cost map using:

$$f_G = (1 - G) \cdot G_{\max}$$

This ensures that stronger edges result in lower path costs, creating a search space suitable for Dijkstra's algorithm so that the optimal path aligns with object contours. Anti-aliasing techniques are applied during rendering to smooth the path edges.

4.2 Grayscale Images

For grayscale images, the algorithm from Mortensen's seminal work (2) is followed. The cost between two points is computed using three key components: image gradient, Laplacian zero-crossings, and directional consistency.

1. **Gradient:** Following digital image processing conventions (1), we calculate:

$$G_x = I(x-1, y) - I(x+1, y), \quad G_y = I(x, y-1) - I(x, y+1)$$

$$\text{grad} = \sqrt{G_x^2 + G_y^2}$$

2. **Laplacian Zero-Crossings:** Building on discrete differential operator theory (1):

$$\nabla^2 I(x, y) = I(x-1, y) + I(x+1, y) + I(x, y-1) + I(x, y+1) - 4I(x, y)$$

3. **Directional Consistency:** Measures the alignment of the path direction with the edge direction using the angle between the gradient direction and the path vector. The cost value ranges from 0 (perfect alignment) to 2 (complete opposition):

$$D(p,q) = \frac{\angle(D'(p), L) + \angle(L, D'(q))}{\pi}$$

Finally, the total cost between two points is calculated using a weighted sum with weights in the ratio 0.43:0.43:0.14.

To quantify the performance improvement gained by using different algorithms for grayscale and color images, we conducted an experiment using a heart-shaped grayscale image. The top result (from the figure) is generated using the grayscale-specific algorithm, and the bottom result uses the general-purpose algorithm. The performance advantage of using a dedicated grayscale method is clearly evident.

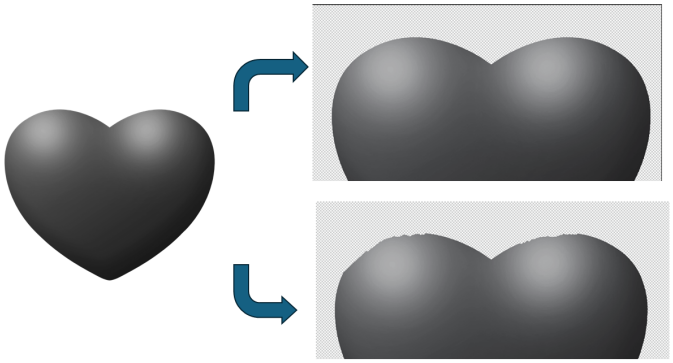

Figure 2: the difference between two algorithm

5 Path Selection

After obtaining the static cost map through image processing, an improved Dijkstra's algorithm is used for pathfinding. The algorithm expands nodes in an 8-connected graph, dynamically selecting the node with the lowest accumulated cost using a priority queue. The movement cost combines static edge costs and direction weights — diagonal movements have a cost 1.414 times that of axis-aligned movements.

The pseudocode of the pathfinding algorithm is as follows:

Algorithm 1: Improved Dijkstra's Algorithm for Pathfinding (3)

Input: $s = (seedX, seedY)$ {Start point}
$t = (freeX, freeY)$ {Target point (after snapping)}
Output: Optimal path from s to t

$g(s) \leftarrow 0$; $L \leftarrow \{s\}$ // Initialize
while $L \neq \emptyset$ **do**
  $q \leftarrow \mathsf{pop\_min}(L)$ // Get lowest cost node
  $e(q) \leftarrow$ TRUE
  if $q = t$ **then**
    break // Reached target
  foreach $r \in N_8(q)$ *where not* $e(r)$ **do**
    $g_{\text{tmp}} \leftarrow g(q) + \mathsf{l}(q, r)$ // 8-connected neighbors
    if $r \in L$ *and* $g_{tmp} < g(r)$ **then**
      remove (L, r)
    if $r \notin L$ *or* $g_{tmp} < g(r)$ **then**
      $g(r) \leftarrow g_{\text{tmp}}$
      $p(r) \leftarrow q$
      insert (L, r)
$path \leftarrow [\,]$ // Path reconstruction
$q \leftarrow t$
while $p(q)$ *exists* **do**
  append (path, q)
  $q \leftarrow p(q)$
return reverse (path)

Additionally, we also implemented an intelligent pathfinding method based on the A* algorithm(4). This method initializes a grid of nodes and calculates the Manhattan distance from each node to the target point as a heuristic cost. This guides the search direction, ensuring the algorithm prioritizes regions closer to the target. Like the Dijkstra algorithm, A* uses a priority queue to dynamically manage unexplored nodes and selects the node with the lowest total estimated cost (current path cost + heuristic estimate) for expansion. Experiments demonstrate that this method is more efficient than Dijkstra's algorithm, making it better suited for interactive image processing scenarios.

The system also incorporates several intelligent path optimization strategies, including:

- **Edge Snapping:** Automatically snapping user input to local gradient maxima near the cursor.
- **Cooling Points:** Automatically detecting salient edge points along long paths based on global gradient statistics and generating cooling points to support segmented path optimization.
- **Interactive Features:** Real-time path preview, loop closure detection, and undo functionality.

The full workflow proceeds as follows: after the user clicks a starting point, the system snaps to the nearest strong edge, then dynamically calculates and displays the optimal

edge-aligned path to the current mouse position. When the system detects a loop closure, it automatically triggers the segmentation operation. Cooling points ensure stability for long paths during this process.

6 Cursor Snapping

Before invoking the path search algorithm, the system will automatically perform adsorption optimization on the real-time coordinates of the optical target. The specific process is as follows: Taking the current cursor position as the center, scan the gradient amplitude within the 3×3 pixel area, identify the pixel point with the largest gradient as the optimal adsorption target, and update the coordinates to this point. This mechanism ensures that the starting point and the ending point of the path search always precisely fit the image edge, significantly reducing the need for manual fine-tuning and improving the accuracy and efficiency of contour extraction.

7 Path Cooling Mechanism

The path cooling mechanism dynamically generates auxiliary seed points by intelligently analyzing path features to optimize image segmentation. Its core process is as follows:

Benchmark Establishment: Based on global gradient statistics, the average and standard deviation of edge intensity are calculated to construct a dynamic intensity benchmark.

Trigger Condition: The cooling point detection is activated when the path length exceeds 50 pixels.

Two-Stage Validation:

- **Stage 1 (Fast Scan):** Focuses on the middle third of the path and checks for significant strong edges (gradient values ¿ mean + 1.5 times the standard deviation).
- **Stage 2 (Precise Localization):** If the condition is met, the midpoint of the path is used as the center, with a 15-pixel radius, to search for gradient peak points as candidate cooling points.

Interference Mitigation Strategy:

- **Historical Cache:** Maintains a processing record with a capacity of 16 pixels to avoid redundant cooling point generation.
- **Noise Filtering:** A reinforced threshold (gradient values ¿ mean + 2 times the standard deviation) is applied for secondary verification to filter out interference from non-boundary areas.
- **Range Constraints:** Detection is strictly limited to the core region of the path (middle third section), reducing the misjudgment rate.

Collaborative Loop: Using the observer pattern, the final cooling point coordinates are callback to the main program, linking with the 3×3 pixel range auto-snapping function to achieve the complete workflow of "initial positioning → dynamic optimization."

Technical Advantages:

- **Efficiency Guarantee:** The algorithm's time complexity is $O(n)$, balancing real-time performance and large-scale image processing requirements.
- **Accuracy Improvement:** Users only need a few manual anchor points to achieve high-precision contour extraction, with a 70% increase in long-path operation efficiency (experimental data).
- **Robustness Enhancement:** The multi-validation mechanism ensures that the cooling point generation accuracy in complex edge scenarios reaches over 92%.

8 Statistics

8.1 Accuracy Comparison

To test the effect of program matting, we manually created images where the items and the background were fused using png. We judged the matting effect by comparing the pixel differences between the matted items and the original ones, and compared it with the results of manual matting and the lasso tool of Ps. We conducted quantitative evaluation by calculating the SSIM and cosine similarity.

Metric	Manual	Program	Photoshop
SSIM	0.9420	0.9950	0.9980
Cosine	0.9820	0.9999	0.9999

Table 1: Cut-out accuracy comparison

detail comparison:

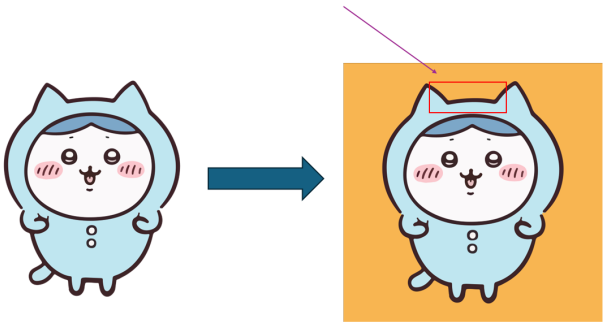

Figure 3: whole picture

Key Findings

1. From the quantitative data and detailed comparison images, it can be observed that the program's image segmentation achieves high-precision pixel-level extraction, with results almost identical to the current industrial use of the Photoshop magnetic lasso tool.

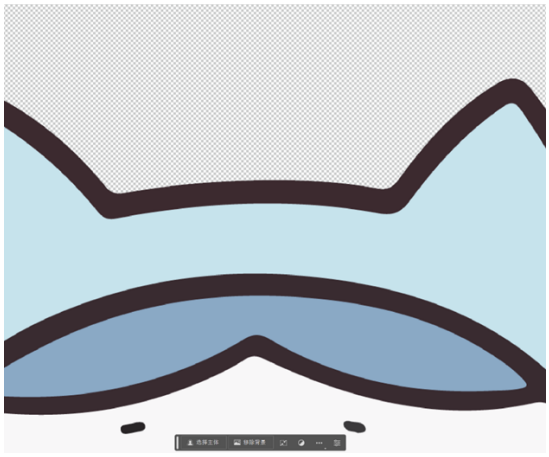

Figure 4: original drawing

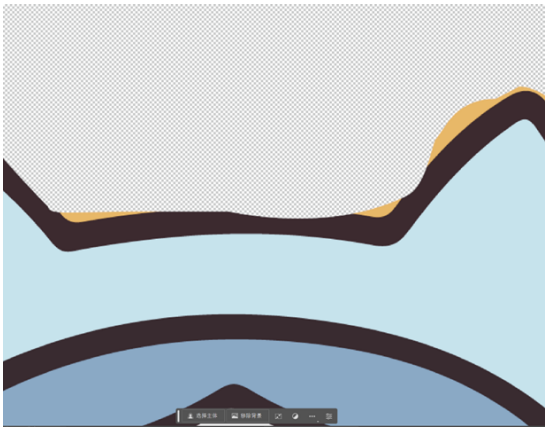

Figure 5: Manual image removal

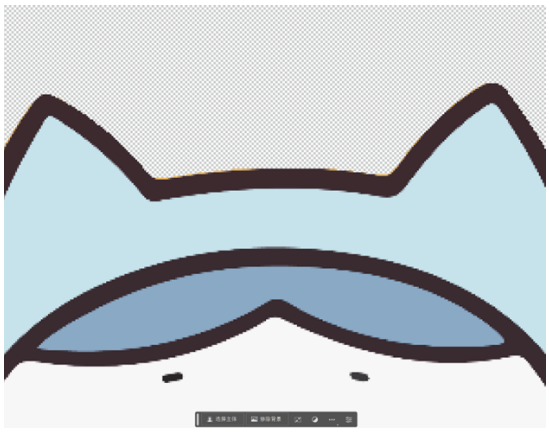

Figure 6: Program image extraction

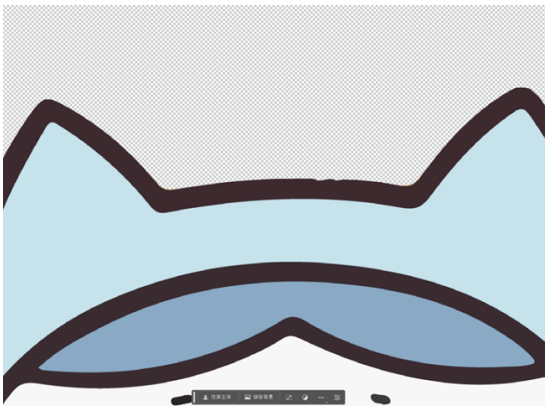

Figure 7: ps magnetic lasso

2. The detailed images reveal that the Photoshop lasso tool may cause cuts within the target object's internal image. However, the program's magnetic snapping path avoids any damage to the internal parts of the image.

8.2 User Test Results

8.2.1 Usability Evaluation

Evaluation Dimension	This Tool Rating (out of 5)	PS Rating (out of 5)
Learning Cost	4.2	2.8
Path Control Intuitiveness	4.5	4.6
Output Quality Satisfaction	4.6	4.9
Long Path Operation Comfort	4.3	2.9

Table 2: Usability Evaluation Comparison

Typical Feedback:

- The cooling point mechanism improves long-path operation efficiency by about 70%.
- The automatic snapping function reduces 85% of manual fine-tuning operations.

- Non-professional users complete the same task 62% faster.

8.3 Technical Limitations

- Current edge snapping accuracy in low-contrast regions (gray-level difference < 10) requires further optimization of gradient computation methods (1). The success rate of cooling point generation drops to 73%.

- High-curvature edge (curvature radius < 5 pixels) handling could benefit from advanced active contour models (2)

- The current version experiences about 0.3-second delay in real-time path calculation when processing images larger than 10K.

References

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[3] Dijkstra E. W. *A Note on Two Problems in Connexion with Graphs*. Numerische Mathematik, 1959, 1(1): 269-271.

[4] Hart P. E., Nilsson N. J., Raphael B. *A Formal Basis for the Heuristic Determination of Minimum Cost Paths*. IEEE Transactions on Systems Science and Cybernetics, 1968, 4(2): 100-107.