Weekly Report: Content Aware image Resizing

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I. Analysis of Base Algorithm

Based on our implementation, we analyzed the performance and visual quality of the standard seam carving algorithm [1]. We used images from the RetargetMe benchmark [2] for a standardized comparison.

A. Strengths

- **Content Preservation:** The algorithm is highly effective on natural landscapes and images with clear, textured backgrounds. It removes pixels from areas like sky, sea, or fields without noticeable distortion.
- **Simplicity and Efficiency:** The dynamic programming approach is simple and computationally efficient for a single seam removal ($O(rc)$).
- **Flexibility:** The algorithm is inherently flexible, allowing for both width and height reduction, as well as content-aware enlargement.

B. Limitations and Observed Artifacts

- **Distortion of Straight Lines:** The algorithm's primary weakness is its tendency to distort or bend straight lines, particularly in architectural images or images with strong geometric patterns. As seams are removed, nearby pixels shift, causing lines to "wave." We are trying to overcome this effectively.
- **Coherence of Large Objects:** If an important object (e.g., a person's face) is large and spans a significant portion of the image, the algorithm may identify seams that pass through it, especially if it contains low-energy regions, which might lead to distortion in the face (which is an important region). In order to change this, as recommended by Prof. Raval in the mid-semester presentation, we have to design the algorithm so that it focuses on environment rather than the main components of the image.
- **Cumulative Artifacts:** When many seams are removed, the image becomes much more pronounced. Objects can become visibly distorted.

II. Energy Function Experimentation

A key part of our work was to evaluate different energy functions. The choice of function directly controls which pixels are candidates for removal.

TABLE I
COMPARISON OF ENERGY FUNCTIONS

Filter	Description	Observed Effect on Seam Selection
Sobel	First-order derivative (gradient magnitude). Approximates the gradient.	It worked well for general-purpose edge detection.
Prewitt	Similar to Sobel but with a simpler kernel. Also a first-order derivative.	Results were visually almost identical to Sobel. It is slightly less sensitive to diagonal edges but this was not obvious in our tests.
Laplacian	Second-order derivative. Detects lines and isolated points.	This function was very sensitive to noise. It created high-energy maps that were "spotty," sometimes failing to protect smooth but important objects.

III. Proposed Modifications and Future Work

To address the limitations identified in Section I, we tried to implement and evaluate two significant modifications to the base algorithm. These methods rely on dynamic programming and classical computer vision techniques.

A. Forward Energy Computation

The standard algorithm's energy function $e(i, j)$ measured the importance of a pixel before it was removed. It did not account for the new "unnatural" edges that are created after the seam is removed (i.e., when pixel $(i, j-1)$ becomes adjacent to $(i, j+1)$). This is the primary cause of cumulative artifacts.

We will implement the Forward Energy method. This approach modifies the dynamic programming cost function to include the energy that will be introduced by removing a pixel. The cost $M(i, j)$ will be a function not only of $e(i, j)$ but also of the energy cost of creating a new horizontal edge, e.g., $|I(i, j-1) - I(i, j+1)|$. This should prevent the algorithm from creating high-energy artifacts and lead to much cleaner results when many seams are removed.

B. Object Protection Masks

The second limitation is the algorithm's tendency to cut through low-energy parts of important objects (like faces or text). To prevent this, we will introduce object protection masks.

1) **Saliency-Based Masks:** We will experiment with classical (non-DL) saliency detection algorithms (e.g., Itti-Koch-Niebur or spectral residual methods) to automatically generate a "saliency map" of the image.
2) **Hybrid Energy Function:** This saliency map (S) will be combined with the gradient energy (E_{grad}) to create a new hybrid energy map:

$$E_{hybrid} = w_1 \cdot E_{grad} + w_2 \cdot S$$

By assigning a high weight (w_2) to salient regions, we can drastically increase the "cost" of seams that try to pass through important objects, forcing the algorithm to find paths around them.

C. Action Plan

1) Implement the forward energy cost function within our dynamic programming framework.
2) Integrate a classical saliency detection algorithm to generate protection masks.
3) Create and tune the hybrid energy function.
4) Perform a comparative analysis: run the base algorithm, the forward energy algorithm, and the hybrid energy algorithm on the same set of difficult images (e.g., portraits, architecture) from the RetargetMe dataset.
5) Document the visual improvements and any performance (speed) trade-offs.

REFERENCES

[1] S. Avidan and A. Shamir, "Seam carving for content-aware image resizing," *ACM Trans. Graph.*, vol. 26, p. 10–es, July 2007.
[2] M. Rubinstein, D. Gutierrez, O. Sorkine, and A. Shamir, "A comparative study of image retargeting," *ACM Trans. Graph.*, vol. 29, Dec. 2010.