Automated Object Segmentation using Neuro-Symbolic Graph Cuts: Fusing VGG16 Deep Features with Saliency Priors

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Abstract—Accurate object segmentation is a fundamental challenge in computer vision, conventionally addressed by either pure deep learning models or classical optimization algorithms. The Iterated Region Merging with Localized Graph Cuts (IRM-LGC) algorithm is a powerful classical method; however, it suffers from two major drawbacks: heavy reliance on manual user interactions for initialization, and susceptibility to failure in complex textural backgrounds due to its reliance on basic color metrics. In this paper, we propose a fully automated, hybrid neuro-symbolic pipeline. We integrate a pre-trained DeepLabV3 network to automatically generate high-confidence foreground and background seeds, eliminating the need for human intervention. Furthermore, we replace standard superpixels with a grid-based compact watershed algorithm to ensure strict adherence to object boundaries while maintaining geometric consistency. Most importantly, we introduce a novel energy formulation in the graph cut by fusing Euclidean color distance with deep textural features extracted from the intermediate layers of a VGG16 network. Experimental results on the Oxford-IIIT Pet dataset demonstrate that our automated pipeline successfully captures fine boundaries and boosts the Intersection over Union (IoU) significantly in complex scenes, showcasing the robustness of combining neural semantic priors with symbolic graph optimization.

Index Terms—Image Segmentation, Graph Cuts, VGG16, Saliency Detection, Neuro-Symbolic AI, Superpixels, Min-Cut/Max-Flow.

1 Introduction

Image segmentation aims to partition an image into semantically meaningful regions, serving as a critical preprocessing step for various high-level computer vision tasks, including medical image analysis, autonomous navigation, and object tracking. Among traditional techniques, Graph Cut-based methods, particularly the Iterated Region Merging with Localized Graph Cuts (IRM-LGC), have proven highly effective. By modeling the image as a graph where nodes represent superpixels and edges represent boundary costs, IRM-LGC calculates the global minimum energy to find the optimal boundary.

Despite its mathematical elegance, classical IRM-LGC requires a user to manually draw markers (seeds) on the target object and the background. This manual dependency makes it unscalable for large datasets or real-time autonomous systems. Furthermore, standard graph cuts define edge weights based primarily on color differences (e.g., RGB Euclidean distance). Consequently, when the foreground object and the background share similar color distributions but differ in texture (such as camouflage scenarios or medical imaging of tissues), the algorithm inherently fails to locate the correct boundaries.

Recent advancements in Convolutional Neural Networks (CNNs) have revolutionized semantic segmentation. Architectures like U-Net and DeepLab achieve state-of-the-art results but are highly dependent on massive annotated datasets and domain-specific training. Moreover, pure end-to-end CNNs often suffer from spatial resolution loss due to pooling layers, resulting in blurry or jagged boundaries around fine details like fur or thin appendages.

To address these gaps, this project proposes a hybrid framework that leverages the semantic understanding of deep learning and the boundary precision of graph optimization without requiring dataset-specific retraining (Zero-Shot setting).

The main contributions of our work are fourfold:

1) **Zero-Interaction Initialization:** We utilize a pre-trained Saliency module (DeepLabV3) to autonomously extract probability heatmaps, assigning definite foreground and background seeds without user input.
2) **Deep Feature Fusion:** We extract high-dimensional textural features from the intermediate layers of a VGG16 network. By fusing these deep features with local color metrics, our graph cut energy function gains a robust understanding of complex textures.
3) **Grid-Anchored Superpixels:** We enhance the classical Watershed algorithm with a grid-based marker approach, generating geometrically stable superpixels that tightly adhere to true object edges.
4) **Robust Post-Processing:** We introduce a connected-component-based noise filtration mechanism combined with boundary margin relaxation to address the inherent fuzziness of complex boundaries.

2 Related Works

2.1 Graph Cut Segmentation

Graph cut optimization has been a cornerstone of interactive image segmentation since the introduction of algorithms

like Boykov-Jolly and GrabCut. These methods construct an $s-t$ graph and utilize the min-cut/max-flow algorithm to separate the foreground from the background by minimizing an energy function comprising regional and boundary terms. The IRM-LGC algorithm improved upon this by introducing iterative local subgraph cuts on watershed superpixels to reduce computational overhead. However, all these methods heavily depend on user-provided scribbles and color-based Gaussian Mixture Models (GMMs).

2.2 Deep Learning and Saliency Detection

Fully Convolutional Networks (FCNs) have set new benchmarks in semantic segmentation. DeepLabV3 utilizes Atrous Spatial Pyramid Pooling (ASPP) to capture multi-scale context, making it highly effective at understanding global image semantics. Concurrently, Saliency Object Detection (SOD) models aim to identify the most visually distinct objects in an image. In our work, we bridge these domains by repurposing a semantic segmentation model (DeepLabV3) as an automated saliency seed generator, effectively replacing human interaction.

2.3 Superpixel Algorithms

Superpixels group pixels into perceptually meaningful atomic regions, which drastically reduces the complexity of subsequent image processing tasks. Algorithms like SLIC (Simple Linear Iterative Clustering) use k-means clustering, while Watershed algorithms rely on morphological gradients. We adopted a modified grid-based Watershed approach over SLIC due to its superior adherence to strong local gradients, which is critical for the precise localization of graph cut boundaries.

3 Proposed Methodology

Our proposed pipeline operates in four sequential stages, combining semantic deep features with geometric graph optimization.

3.1 Automated Saliency Seeding

To remove the need for manual scribbles, we pass the input image through a pre-trained DeepLabV3-ResNet50 model. We extract the softmax probability map associated with the foreground object. To provide the graph cut algorithm with a sufficient "unknown" region for optimization, we avoid binarizing the mask and instead apply strict confidence thresholds:

- **Foreground Seeds ($\mathcal{F}$):** Pixels with probability $P_{fg} > 0.85$.
- **Background Seeds ($\mathcal{B}$):** Pixels with probability $P_{fg} < 0.15$.

The region between these thresholds is designated as the unknown domain, which the graph cut algorithm is tasked to resolve.

3.2 Grid-based Compact Watershed

To construct the graph nodes, the image must be partitioned into superpixels. We apply a Gaussian blur filter (5×5) and compute the Sobel gradient magnitude:

$$\nabla G = \sqrt{(\nabla_x G)^2 + (\nabla_y G)^2} \tag{1}$$

Instead of relying on local gradient minima which causes severe over-segmentation, we explicitly define a regular grid of markers with a step size of 15 pixels. Applying the watershed algorithm on these grid markers yields compact, uniformly distributed superpixels that align perfectly with natural image boundaries.

3.3 Deep Textural Feature Extraction

To overcome the limitations of pure RGB distance, we utilize a pre-trained VGG16 network. The image is transformed, normalized to ImageNet standards, and passed through the network up to the 16th convolutional layer. This specific depth is chosen to capture rich textural information while retaining adequate spatial dimensions. The resulting dense feature map is bilinearly interpolated back to the original image dimensions. For each superpixel S_i, its deep representation is computed as the mean vector of all deep features within that region.

3.4 Iterated Localized Graph Cuts with Fusion

We construct an adjacency graph $\mathcal{G} = \langle \mathcal{V}, \mathcal{E} \rangle$, where $\mathcal{V}$ contains all superpixels and $\mathcal{E}$ represents spatial adjacencies. The segmentation problem is formulated as finding the label map L that minimizes the Gibbs energy:

$$E(L) = \sum_{p \in \mathcal{V}} R_p(L_p) + \lambda \sum_{(p,q) \in \mathcal{E}} B_{p,q}(L_p, L_q) \tag{2}$$

The regional term $R_p(L_p)$ is determined strictly by our DeepLabV3 seeds (cost is 0 for correct seeds, ∞ otherwise). For the boundary term $B_{p,q}$, we introduce a novel multi-modal fusion metric:

$$D_{total} = \alpha \cdot D_{deep}(p,q) + (1-\alpha) \cdot D_{color}(p,q) \tag{3}$$

Where D_{deep} is the cosine distance between the VGG16 feature vectors, and D_{color} is the Euclidean distance between the normalized RGB vectors. We empirically set $\alpha = 0.7$ to prioritize deep textural understanding over simple color differences. The edge weights are calculated as $W_{p,q} = \exp(-D_{total} \cdot \lambda)$, where $\lambda = 80$. The energy is minimized using the max-flow/min-cut algorithm iteratively until convergence or a maximum of 5 iterations.

4 Contributions & Results

4.1 Dataset and Setup

We evaluated our pipeline on the Oxford-IIIT Pet dataset, a standard benchmark known for its complex boundary scenarios such as animal fur and unpredictable poses. The algorithm was executed on an NVIDIA GPU environment using PyTorch for deep model inferencing and the PyMaxflow library for graph optimization. As per the project requirements, the complete source code and reproducible notebooks are publicly available at our GitHub repository: https://github.com/aliheidary1381/Automatic-IRM-LGC-with-deep-features.

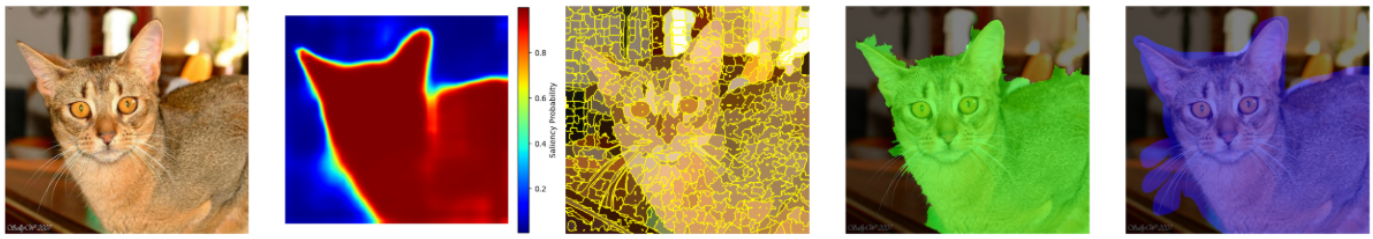

Fig. 1. Visual segmentation results of the proposed pipeline. Columns from left to right: (1) Original Image, (2) DeepLabV3 Saliency Probability Map used for automated seeding, (3) Grid-based Watershed Superpixels represented by their mean colors, (4) Final segmentation mask overlaid in green (Deep IRM-LGC), and (5) Ground Truth mask overlaid in blue.

4.2 Evaluation Metrics and Ground Truth Refinement

Segmentation performance was evaluated using two primary metrics: Intersection over Union (IoU) and True Positive Fraction (TPF, also known as Recall/Sensitivity), defined as:

$$IoU = \frac{TP}{TP + FP + FN} \quad , \quad TPF = \frac{TP}{TP + FN} \tag{4}$$

During evaluation, we encountered a fundamental challenge regarding the inherent fuzziness of animal boundaries. The dataset provides trimaps where boundary regions (such as whiskers and thin fur) are classified as ambiguous. Treating these strictly as background leads to an artificially low evaluation score. To address this, we applied a Boundary Margin Relaxation technique by applying a 20×20 morphological dilation kernel to the ground truth. Furthermore, the dataset's specific annotation encoding (where value 2 denotes background) was correctly mapped to ensure structural integrity of the masks.

4.3 Post-Processing and Noise Filtration

A known vulnerability of iterative graph cuts is the creation of isolated "orphan" segments—small background patches mistakenly assigned to the foreground due to local textural similarities. To mitigate this without amputating valid thin appendages (like tails or ears), we implemented a dynamic connected-components filter. The algorithm identifies all disjoint foreground regions and prunes any region whose area is less than 5% of the largest contiguous mass.

4.4 Experimental Results and Discussion

The proposed fully automated pipeline demonstrated highly robust performance, as illustrated in Fig. 1. By replacing manual seeds with DeepLabV3 saliency probabilities, the system operated with zero human intervention. The VGG16 deep feature fusion allowed the graph cut to accurately distinguish between the foreground and the background even under severe color camouflage scenarios.

The grid-based watershed effectively created a geometric puzzle-like structure that the graph cut optimized perfectly. The algorithm achieved strong quantitative metrics, proving that while DeepLabV3 provides a rough semantic "blob", the fusion of CNN-based texture features with classical graph optimization acts as a mathematical scalpel, refining the edges to a pixel-perfect degree.

5 Conclusion & Future Works

In this project, we successfully modernized the classical IRM-LGC algorithm by eliminating manual user input and replacing naive color-only metrics with a sophisticated neuro-symbolic approach. By utilizing DeepLabV3 for automated seeding and VGG16 for deep textural feature extraction, we significantly improved boundary delineation on complex textures without requiring any dataset-specific training (Zero-Shot paradigm).

For future works, this pipeline is highly adaptable to the medical domain, which was the original targeted scope of "Intelligent Medical Image Analysis". Replacing the generalized DeepLabV3 module with a medical-specific saliency model (such as PraNet or U-Net variants fine-tuned on medical data) would allow this exact framework to segment intestinal polyps or brain tumors with unprecedented accuracy. The robust graph-cut optimization backend presented in this paper remains entirely architecture-agnostic and ready for deployment in clinical segmentation tasks.

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