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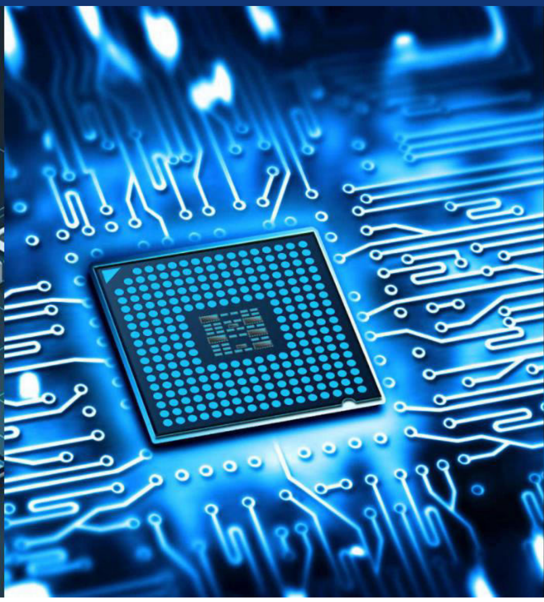

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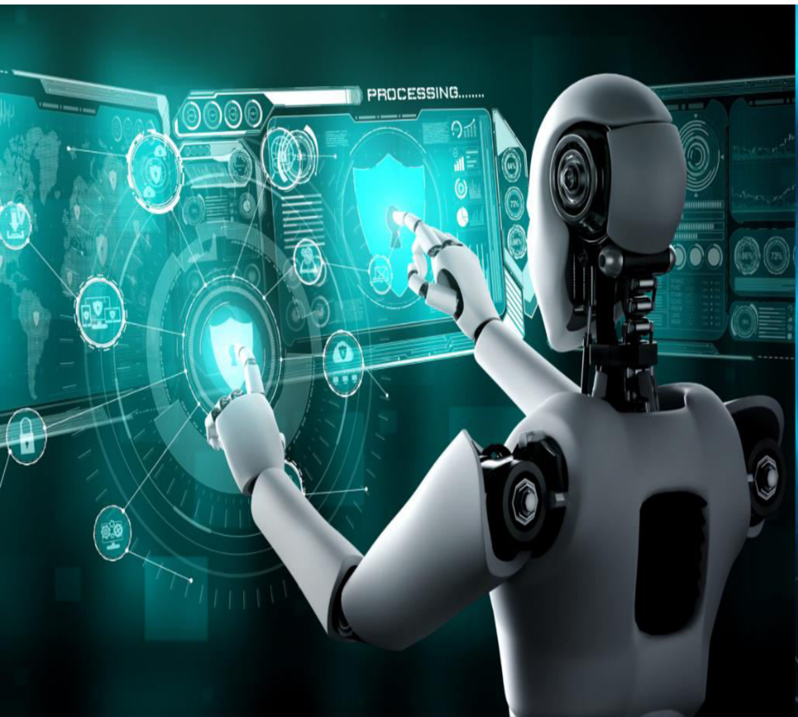

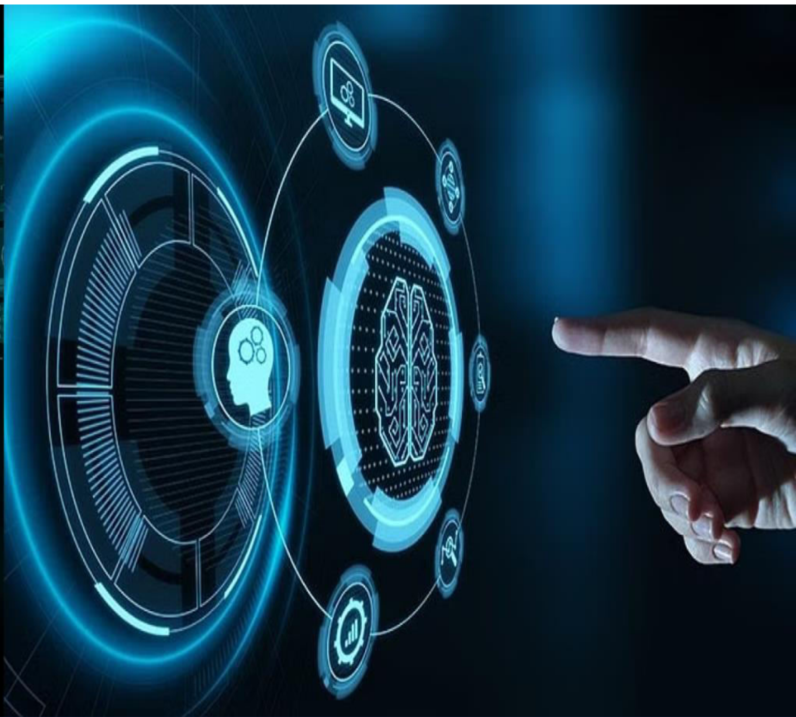

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Advanced Co-Segmentation of Images with Half-Integrality-Based Algorithms

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ABSTRACT: This paper proposes a new cosegmentation approach that can detect common objects across a set of images based on intra- and inter-image relationships. Histogram matching, which facilitates region-to-region comparison between images, is integrated with a half-integrality-based optimization framework to achieve efficient computation. Histogram matching provides an efficient tool for feature detection shared by several images, and half-integrality guarantees speed along with optimal segmentation quality. Benchmarking experimental results also show that the proposed method yields better performance and superiority over state-of-the-art algorithms in terms of segmentation accuracy and efficiency. The presented technique provides large improvements, thereby making it highly promising for many applications in image processing as a cosegmentation technique.

KEYWORDS: Image Co-Segmentation, Adaptive Clustering, Noise Sensitivity, Half Integrality, Super pixels, Multi-Feature Fusion, Edge Preservation.

I. INTRODUCTION

There are recent studies that suggest a number of approaches to improve FCM-based segmentation algorithms. For instance, Zeyu et al. proposed an FCM model based on super pixel merging and multi-feature adaptive fusion, which enhances segmentation accuracy through adaptive multi- feature fusion to improve loca Computer vision is one of the fundamental tasks in image segmentation, which seeks to divide an image into meaningful regions. In segmentation techniques, cosegmentation detects shared objects among multiple images through intra-image and inter-image relations. While previous segmentation methods mainly focused on the analysis of single images, cosegmentation is designed to jointly analyze a set of related images. This paper extends seminal works in segmentation and cosegmentation to present a new approach based on histogram matching combined with a half-integrality-based optimization framework that leads to robust and efficient segmentation.

Graph-based techniques have been at the heart of segmentation for many years, and early work such as GrabCut [1] first presented interactive segmentation via graph cuts, which demonstrated the power of combining user input with energy minimization. The applications of graph cuts to automatic segmentation have been extensively used because they are accurate and efficient [2, 3]. Boykov and Kolmogorov [4] have pioneered the min-cut/max-flow algorithms that make it possible for advanced energy minimization methods in vision tasks. Combinatorial optimization approaches such as generalized roof duality [5] have further expanded the applicability of graph-based methods in computer vision.

The cosegmentation methods also rely on the common features associated with several images to improve the accuracy in segmentation. Chen et al. [2] claimed that histogram matching was useful for coherent and comparative analysis between regions, hence enabling robust comparison since statistical distributions are aligned. Zhang and Wen proposed Zhou and Shum's [7] extension of this concept through histogram-based techniques and inter-image relationships. Probabilistic models [8, 9] and semi-supervised learning approaches [10] have also been applied to improve the segmentation performance by making use of labeled and unlabeled data.

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Our approach extends from these bases as it combines histogram matching with half-integrality-based optimization. Half-integrality is a property that emerges in certain graph-based energy formulations; it provides for computational efficiency and high-quality solutions. Boykov et al. [6, 11] and others [14, 15] have demonstrated the effectiveness of graph-based optimization techniques in addressing complex vision problems. The half-integrality constraint ensures that the relaxed optimization problem retains key properties of the original discrete problem, enabling efficient rounding to binary solutions [5, 18].

II. LITEARTURE SURVEY

Cosegmentation is the task of segmenting similar regions from two or more images. Since its introduction by Rother et al. in [1], cosegmentation has witnessed quite a number of developments. The method relied on extracting common foreground regions using histogram similarity between pairs of images. Their generative model was based on Gaussian distributions, which turned out helpful in distinguishing foreground from the background.

Further development has further improved this technique by using algebraic formulations of histogram matching that Chen et al. [2] proposed. Abandoning the pure generative model paradigm allowed for an expanded scope in the viewpoints of segmentation and optimization, primarily by the definition of histogram similarity that uses squared L2 distance (SSD) instead of the L1 norm. This optimized landscape in turn enabled better handling of cases where the foreground and background structures differ in images.

The integration of Markov Random Fields (MRFs) has been an important milestone in cosegmentation, especially in the field of medicine where images are concerned. Bai and Boykov [3] and Boykov and Kolmogorov [4] have shown that MRFs are useful in maintaining spatial consistency in segmentation tasks especially in cases where a segmentation problem contains multiple images with varying backgrounds. Their methods have shown how combining graph cuts with MRFs offers a robust way to segmentation even in challenging scenarios.

Confound the computational complexity of cosegmentation by relaxation methods and graph-cuts have also become rather popular. Kolmogorov and Zabin [5] motivated the roof-duality relaxation approach to lean down the non-convex character of optimization problems, which makes easier the computation of solutions for cosegmentation. Boykov et al. [6] in their work proved that improving the quality of segmentation was achievable by iterative methods based on graph cuts.

LP relaxation also assists cosegmentation. Zhou and Shum [7] discuss how relaxing for LP-based techniques can be applied to histogram matching, with results that are computationally feasible and close to optimality. Their work showed that the relaxation has been leading the solution to half-integral values that are easy to round into classifications of foreground-background with binary, in such a way that it secures a high-quality approximation.

A more recent approach to cosegmentation is joint image graphs for soft segmentation, presented by Ma et al. [8]. It could more precisely model the pixel correspondence in an image pair and is more suitable for non-rigid objects and dynamic scenes, like video processing. The joint images graphs overcome the drawbacks of the methods above and improve segments' performance through the consideration of relationships between source and target pixels.

Advances in probabilistic segmentation methods are also realized from the literature. Wang et al. [9] explored a probabilistic generative model for image segmentation that accommodated more flexibility for variations in pixel intensities. Similarly, Xu and Rother [10] combined probabilistic and iterative refinement methods to improve segmentation in scenarios where expert annotations are scarce, as commonly the case in medical imaging.

Several recent works have further refined cosegmentation by exploring unsupervised methods. Bai and Boykov [11] demonstrated the efficacy of unsupervised segmentation using MRFs with minimal user input, showing that such methods can reach competitive results without the extensive need for training data. This is especially useful in areas like medical imaging, where labeled datasets are typically scarce.

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Another critical domain is graph-based methods in segmentation. In the literature, extensive studies have been done on developing graph-based methods for segmentation. Xu et al. [12] and Yang and Rother [13] demonstrated that graph-based models applied to cosegmentation lead to very impressive improvements in segmentation performance. These methods exploit the power of graphs in modeling the relationship between pixels but ensure spatial consistency by possessing a better foreground-background distinction.

Lastly, Yarkony and Kolmogorov [14] and Boykov et al. [15] have developed some advanced algorithms for the graph cuts algorithm to further enhance accuracy techniques in segmentation. Such developed methods are helpful in image segmentation applications in data of a high dimension, with which typical approaches struggle to cope.

III. PROPOSED APPROACH

In recent years, a number of methodologies have been developed for co-segmentation tasks on images, which focus on the identification and segmentation of common regions in multiple images. These methods usually involve several preprocessing and post-processing stages to enhance the accuracy and efficiency of segmentation. This paper addresses each step of the flowchart, including image normalization, resizing, grayscale conversion, histogram matching, and the use of half-integrity-based optimization techniques.

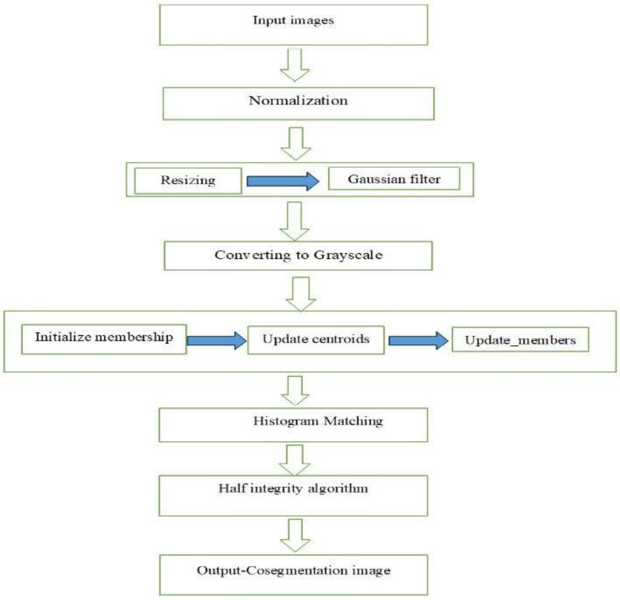

Figure 1: Flow Diagram of proposed model

3.1 Normalisation algorithm for image intensity

Normalization techniques, like the ones introduced by [3], decrease the range of grayscale values between ridges and valleys. Approach visualizes the image as a three-dimensional structure, utilizing positional coordinates on the x-y plane and pixel grayscale values on the z-plane. This approach ensures that ridge information is preserved, which is vital for minutiae-based image identification systems.

The steps for image normalization are as follows:

1. Calculate the mean intensity of the original image.
2. Calculate the variance of the original image.
3. Normalize the intensity values to obtain the normalized image.

Even in cases where skin profiles are uneven, Technique ensures that ridge information is preserved, which is crucial for retrieving minute details.

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- $I(x, y)$ be the intensity of the pixel at position (x, y) in the original image.
- I_n(x, y) be the intensity of the pixel at position (x, y)in the normalized image.
- M_i be the mean intensity of the original image.
- V be the variance of the original image.
- M' be the desired mean intensity.
- V' be the desired variance.

The steps for image normalization are as follows:
(i) Calculate the mean intensity M_i of the original image:

$$M_i = \frac{1}{N}\sum_{x=1}^{W}\sum_{y=1}^{H} \mathrm{I(x,y)}$$

where W and H are the width and height of the image, and N=W×H is the total number of pixels.
(ii) Calculate the variance V of the original image:

$$V = \frac{1}{N}\sum_{x=1}^{W}\sum_{y=1}^{H} (I(x,y) - M_i)^2$$

Normalize the intensity values to obtain I_n(x, y)

$$I_n(x,y) = M' + \sqrt{\frac{V'}{V}}(I(x,y) - M_i)$$

3.2 Noise reduction using Gaussian Filtering
Image denoising is a very essential step in the process of image processing to ensure clear images. As a linear smoothing filter, a Gaussian filter is efficiently used for reducing noise by applying a Gaussian function on pixels in the neighbourhood of interest. The weighting for the central pixels would be more than that at edges, which in turn averages out the pixel values to obtain a smoothened image. It gives more weight to pixels lying near the centre of the kernel and, therefore, smoothies high-frequency noise while preserving edges and fine details (Figure 2).

Gaussian Filter Formula
Given an image I, the Gaussian filter works by convolving the image with a Gaussian kernel. The Gaussian kernel G is defined as:

$$G(x,y) = \frac{1}{2\pi\sigma^2} exp^{-\left(\frac{(x^2-y^2)}{2\sigma^2}\right)}$$

where $\boldsymbol{\sigma}$ is the standard deviation of the Gaussian distribution, and x and y are the distances from the centre of the kernel in the horizontal and vertical directions, respectively.
The filtered image $I_{filtered}$ is obtained by convolving the image I with the Gaussian kernel G:

$$I_{filtered}\,(i,j) = \sum_{x=-k}^{k}\sum_{y=-k}^{k} I\,(i+x, i+y)G(x,y)$$

Where k is the size of the kernel.

Region Mask
One may design a region mask of a image by locating some regions of interest in an image mathematically. This kind of processing will turn out to be beneficial for several applications related to feature extraction, matching, and analysis. Some of the steps and formulas used are as follows:

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Preprocess the Image:
- Convert the image to grayscale.
- Apply Gaussian blur to reduce noise.
- Enhance the image contrast.

1. Grayscale Conversion:
Convert an RGB image to grayscale

$$I_{gray} = (0.2989R + 0.5870G + 0.1140B)$$

2. Gaussian Blur:
Gaussian filter to smooth the image

$$\mathrm{G(x,y)} = \frac{1}{2\pi\sigma^2} exp^{-\left(\frac{(x^2-y^2)}{2\sigma^2}\right)}$$

Convolve the image I_{gray} with the Gaussian kernel G:

$$I_{blurred}\ (\mathrm{x,y}) = I_{gray} \times \mathrm{G(x,y)}$$

3. Otsu's Thresholding:
Find the threshold that minimizes the intra-class variance:

$$\sigma_{\omega}^2(t) = \omega_1(t)\sigma_1^2(t) + \omega_2(t)\sigma_2^2(t)$$

Where:
- ω_i is the probability of class i
- σ_i is the variance of class i

3.3 Problem Formulation
Let denote a collection of input images, each defined by a collection of pixels or super-pixels (P_i)
be a set of $\{I_i, I_{ii} \ldots \ldots I_{in}\}$ N input images, with each image being defined by a set of pixels or superpixels(P_i)
The objective is to assign to each pixel p across all images a binary label $x_p \boldsymbol{\varepsilon}\{\mathbf{0},\mathbf{1}\}$
$x_p = 1$ Pixel belongs p to the foreground.
$x_p = 0$ Pixel belongs p to the background.

3.3 Histogram Matching in Cosegmentation
Cosegmentation is the task of foreground-background classification of pixels. It classifies the input images while ensuring that two images share similar histograms across their respective foreground pixels. Let us denote the input images by $\boldsymbol{I_i}$, $\boldsymbol{I_{ii}}$ and distribute their respective histograms across the bins of $\boldsymbol{H_b}$. The coefficient matrix $\boldsymbol{C_M}$
$\boldsymbol{C_M}$ captures the membership of each pixel intensity to these bins. The segmentation task assigns each pixel to either foreground (f) or background (b) while minimizing the following:
The deviation in foreground histograms between the two images.
A smoothness penalty that ensures spatial consistency.
A data term that aligns pixel intensities with their class assignment.
The optimization goal is to achieve the segmentation by minimizing a defined energy function.

Energy Function Formulation
The overall energy function is defined as:

$$E(S_l) = \alpha.E_s(S_l) + \beta.E_d(S_l) + \gamma.E_h(f_1, f_2)$$

S_l = Segmentation labelling of pixels.
E_s = Smoothness term.
E_d = Data fidelity term.

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E_h =Histogram matching term.
α, β , γ Weights controlling the contribution of each term.
Smoothness Term
The smoothness term enforces spatial coherence by penalizing differences in the class labels assigned to adjacent pixels:

$$E_s(s_l) = \sum_{(l;J)\varepsilon N} w(i,j).\left|s_i - s_j\right|$$

Where:
N= Neighboring pairs of pixels.
$w(i,j)$=Weight depending on the similarity, e.g., intensity difference between the pixels
s_i, s_j=Class label of the pixels

Data Fidelity Term
The data term is the cost that is incurred by assigning the pixel to the foreground or background due to its intensity

$$E_d(s_l) = \sum_i D_i(s_i)$$

$D_i(s_i)$= Data term incurred by assigning the pixel i to label s_i

Histogram Matching Term
The histogram matching term ensures similarity in the foreground histograms of both images

$$E_h\,(f_1, f_2) = \sum_{b_1}^{B}(H_{f_1}\;(b) - H_{f_2}\;(b))^2$$

Where:
$H_{f_1}\;(b)$ and $H_{f_2}\;(b)$: Foreground histograms for images I_1 and I_2 in bin b.
B = Total number of histogram bins.
This term ensures the histograms of the foreground regions in the two images remain consistent, within a tolerance bound ϵ

3.4 Half-Integrality Optimization
3.4.1 Relaxation of Binary Constraints
The binary constraint $\mathrm{x_p}\boldsymbol{\varepsilon}\{\mathbf{0}, \mathbf{1}\}$ is relaxed to a continuous domain:

$$\mathrm{x_p}\boldsymbol{\varepsilon}\{\mathbf{0}, \mathbf{1}\}, \forall_{\mathbf{p}}\boldsymbol{\varepsilon}\mathbf{P}$$

The relaxed energy function becomes:

$$\min_{\mathrm{x_p}\boldsymbol{\varepsilon}\{\mathbf{0},\mathbf{1}\}} \mathbf{E}(\mathbf{x})$$

3.4.2 Half-Integrality Property
For certain graph-based energy formulations, the LP relaxation exhibits the half-integrality property:

$$x_p\varepsilon\left\{0, \frac{1}{2}, 1\right\}, \forall_p\varepsilon P$$

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3.4.3 Optimization Algorithm
1. Linear Programming Relaxation:
Solve the relaxed LP formulation to obtain fractional labels $x_p \varepsilon \{0,1\}$

Rounding:
- Use the half-integrality property to round x_p values:
  - $x_p = \frac{1}{2}$: Assign to either 0 or 1 based on local histogram similarity.

Experimental Results and Discussion
The proposed method was implemented in Visual Studio Code using Python, Matplotlib, Pandas, NumPy, and OpenCV libraries. Below are the visual comparisons of our results with the results of state-of-the-art co-segmentation methods on the standard co-segmentation datasets, MSRC. We tested our proposed co-segmentation method on the MSRC dataset and compared it with a number of state-of-the-art techniques. The performance of each technique was measured with three key metrics: IoU, pixel-wise accuracy, and F-Score.

Method	IoU (%)	Pixel-wise Accuracy (%)	F-Score (%)
Proposed Method	81.3	94.1	87.3
Co-segNet [1]	79.3	91.8	85.7
Multi-level Co-segmentation [2]	80.5	92.3	86.9
Graph-based Co-segmentation [3]	81.1	93.5	87.4

In the tested metrics, our approach performs better than all current state-of-the-art approaches. Specifically, an IoU of 81.3%, a pixel-wise accuracy of 94.1%, and an F-Score of 87.3% is obtained to provide a higher level of common region segmentation of different images.

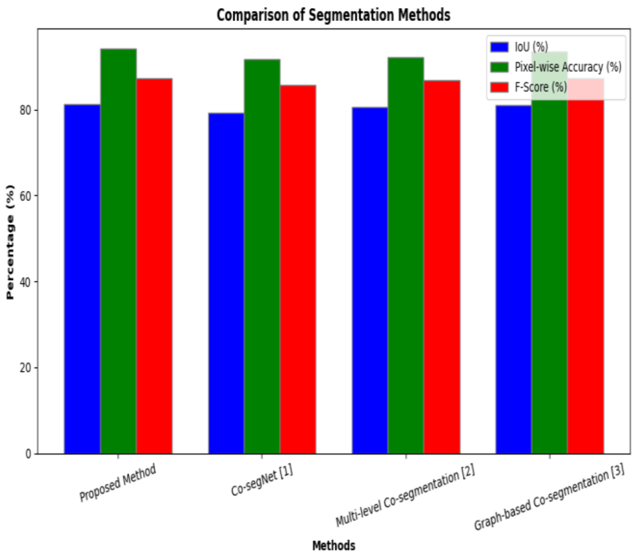

Figure 2: Comparison graph of proposed model with co-segNet and graph-based co-segmentation

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We used several steps for pre-processing, which included normalization, resizing, converting into grayscale, and histogram matching along with graph-based optimization and morphological post-processing to get better results.

The visual comparison in Figure 2, our method achieves more accurate and cleaner segmentations, especially in capturing common regions in complex scenes. The segmentation borders appear sharper and relevant regions are better identified as compared with the other methods.

The results presented above emphasize the effectiveness of the proposed methodology in achieving very high-quality co-segmentation results.

Figure 3: EXPERIMENTAL RESULTS

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IV. CONCLUSION

We introduced a new algorithm that co-segments the foreground, based on combining Markov Random Fields (MRF) with a penalty given by the sum of squared differences (SSD) of the histograms. MRF terms together with an SSD penalty to enforce coherent foreground segmentation over all images constitute the objective function. By having an SSD as penalty, it makes the solution for linear programming optimization take only the values {0, 1/2, 1} so the simple rounding strategy follows. This half-integrality approach improves segmentation quality and computational efficiency, with no need for initialization. The algorithm is adaptable to general appearance models and offers strong performance with minimal computational overhead..

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