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Integrated Approach for Semantic Image Segmentation

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ABSTRACT:
Image segmentation is process of dividing image into set of super pixels. Segmentation is required for an image to perform editing tasks; we have several techniques to perform segmentation but everyone has its own limitations. In this work, we introduce integrated approach for Semantic Segmentation, a combination of both soft semantic segmentation and hard semantic segmentation. In this approach we propose iterative weighting procedure, which neglects outliers during iterations for better hard segmentation and also perform saliency optimization on foreground and background maps to improve quality of segmentation. The proposed approach performs better than existing approaches.

Index Terms— ***Soft Semantic Segmentation, Saliency Optimization;***

INTRODUCTION

Image segmentation is process of dividing an image into segments to better analyze and understand. In semantic image segmentation we assign label to every pixel such that every pixel belongs to particular label, pixels which belong to same label share same features. Sometimes pixel may belong to more than one segment in such cases we use soft segmentation to decompose an image. In soft segmentation, value of segmentation lies between 0 and 1. To speed up semantic image segmentation process reliable pre-segmentation is performed. First of all, pre-segmentation should provide distinct segments of image by representing reliable soft segments. Finally, the segmentation should be done automatically without interference or requirement of expert artist. The previous approaches for semantic segmentation fail to satisfy above qualities.

Selection and composition are important in image managing process. Local adjustments are done with choosing and combining elements from different images in a powerful way to produce new content. But perfect selection is difficult task especially when unclear boundaries and transparency are involved. Segmentation can be done using tools but they only detect low-level features and completely rely on image content for better results. Further, they only generate binary selections that need refinement to account for soft boundaries. Saliency of object is a state in which human eye draws its attention constantly and immediately. It has two features 1) contrast value 2) Background Prior. Suppose, if there are ten people wearing dresses in which nine of them are wearing light color and one wore dark red color then immediately our attention will be drawn onto person wearing dark color dress that is it is stimuli which makes an object stand out from the crowd. In this paper, we introduce (1) a model combining both hard and soft semantic segments (2) an iterative weighting procedure for better hard segmentation by neglecting outliers.

RELATED WORK

Over the years, studies regarding soft and hard segmentation are proposed based on various mechanisms and reviews can be seen in Ref [7]. In this section we briefly discuss related works on different points.

The affinity-based methods, such as closed-form matting, KNN matting, and information-flow matting, define inter-pixel affinities to construct a graph that reflects the opacity segmentations in the image. In

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contrary to natural image matting methods, I rely on dynamically-generated semantic features in defining our soft segments instead of a remap, and generate multiple soft segment divisions rather than foreground segmentation. Even though they appear similar, natural image matting and soft segmentation have fundamental differences. Natural image coursing, with a remap as input, becomes the problem of foreground and background color modeling, may it be through selection of color samples or propagation of color information. Even though saliency models are successful, it rules are still challenging in variety of cases. In order to overcome this limitation deep learning [3,4] have been recently introduced. The mechanism which automatically extracts foreground and background maps in training phase to compute saliency. Note that CNN is also effective for analyzing the image; CNN models also achieved best performances than saliency models in different cases.

Saliency detection methods are divided into bottom-up model [2,3] and top-down model [3]. Bottom-up model focuses on low-level features. Some priors are used for describing the salient objects, such as contrast prior [2], background prior [4], [6], [1], and compactness prior [8]. In addition, there are some other techniques to perform saliency detection, such as frequency domain analysis [5], sparse representation [2]. Top-down requires supervised decisions for better performance. Deep learning techniques describe the ability of saliency detection; some of them are Super CNN [8], and DHSNet [1].

PROPOSED APPROACH

The proposed approach consists of four phases (1) Preprocessing (2) Soft Segmentation (3) Hard Segmentation (4) Saliency Optimization. In Preprocessing, color image is selected and segmented using basic algorithms like threshold and K-MEANS clustering. Regional Extraction is applied on segmented image to abstract various features from specific region rather than entire image to increase computation performance.

Soft segmentation is calculated using undirected-weighted graph and picture background based on contrast feature. Undirected weighted graph is constructed by connecting adjacent super pixels and placing weights on each edge. The output of soft segmentation is foreground maps. In foreground maps, image background is blurred and object is concentrated.

In hard segmentation, we perform multilevel Hierarchal iterative weighting clustering and then apply spatial feature on picture background. The output of hard segmentation is background maps. In background maps, image background is concentrated and objects are blurred. Saliency optimization is performed by applying objective function on both foreground and background maps to get final saliency segmented image.

Algorithm: - Integrated semantic segmentation.
Input: color image
Output: saliency segmented image
Step 1: Image is segmented using K-MEANS.
Step 2: Perform contrast and color feature extraction.
Step 3: Calculate soft segmentation using Fuzzy C Means.
Step 4: Calculate hard segmentation using iterative weighting procedure.
Step 5: Perform saliency optimization on output of soft and hard segmentation

In hard segmentation we use iterative weighing procedure. In iterative weighing procedure partially segmented background maps are taken as input and then we compute weighting value (p) which is used for calculating weighted fusion (WHS).The new weighted maps are assigned to HS. We repeat the process until there is no change in background maps. Algorithm for iterative weighting procedure is given below.

Algorithm: Iterative weighting procedure
Input: -Partially segmented background maps{$HS_{(1)}$, $HS_{(2)}$,…., $HS_{(N)}$}
Output: - Integrated background maps **HS**
step:1 **WHS ← ϕ,HS ← ϕ**

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step:2 **HS** $\leftarrow$ **1/N** $\Sigma^{N}_{i=1}$**HS[i]**//Linear fusion
step:3 Repeat {
step:4 for (i=1 to N) {
step:5 **p =**
step:6 **(HS[i]- HS'[i]) (HS - HS`) / (HS[i]- HS'[i],)$^2$(HS-HS `)^2**//weighting value computation
step:7 }
step:8 **WHS** $\leftarrow$ **1/N** $\Sigma^{N}_{i=1}$**HS[i]p**//weighted fusion
step:9 if **HS = WHS**then
step:10 break
step:11 else **HS**$\leftarrow$**WHS** //updating integrated background map
step:12 end
step:13 }
step:14 **HS**$\leftarrow$**Normalization (HS)**
step:15 Return **HS**

RESULT ANALYSIS

In proposed approachaccuracy and recall are analyzed. As number of super pixel increases, processing time also increases, results show that our approach achieved good performance than existing approaches.

Recall refers to percentage of total relevant results correctly classified by your algorithm.For example, a picture has '12' apples and rest are oranges and algorithm identify only '8' apples in picture and out of '8' identified apples only '5' are apples and rest are oranges then recall is 5/12.

Recall = [Truly positive/ predicted results]

Accuracy = [True positive + True negative/Totalitems]

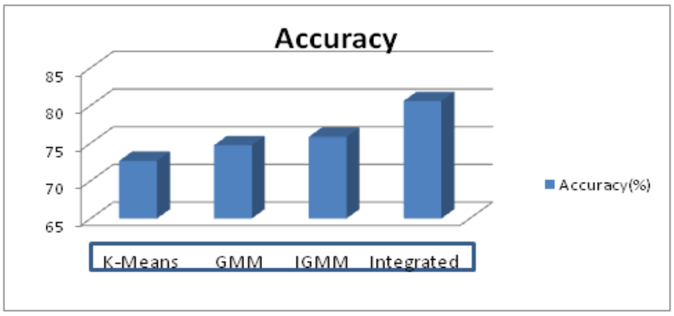

Fig 1: Accuracy

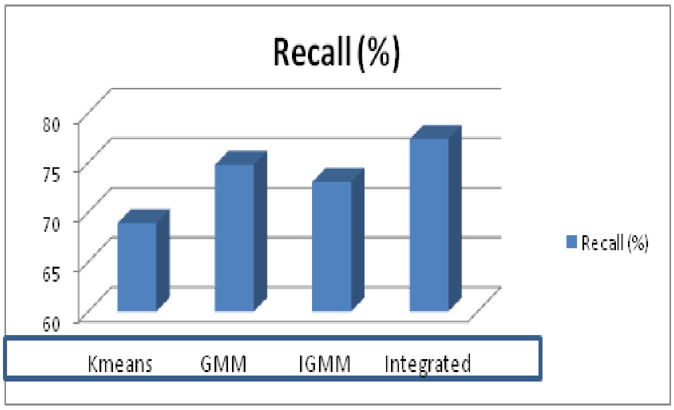

Fig 2:Recall

CONCLUSION

In this paper, we proposed an Integrated approach combining soft segmentation and hard segmentation. In particular, we introduced iterative weighting procedure by neglecting outliers to decrease the amount of noise. In addition, we performed saliency optimization on both foreground and background maps using objective function. Proposed approach has better performance than existing approaches.

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