Object Identification For Computer Vision using Image Segmentation

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Abstract— **Object detection for computer vision is one of the key factors for scene understanding. It is still a challenge today to accurately determine an object from a background where similar shaped objects are present in a large number. In this paper we proposed a method for object detection from such chaotic background by using image segmentation and graph partitioning. We build a "feature set" from the original object and then we train the system using the "feature set" and graph partitioning on the chaotic image. Testing is done on computer manipulated images and real world images. In both the cases our system identified the search object among other similar objects successfully.**

Keywords-Computer vision; Image processing; Image segmentation; Graph partitioning

I. Introduction

Image Segmentation for object detection is the most vital part of computer vision where the computer has to identify objects differently from the background whether it is a face or hand or a man or simply static objects.

If the contrast difference of the background with the foreground is high then the detection is simple. But if the background is chaotic and there is a little difference between the background and the object then it becomes difficult for the system to identify the edges from the background. The major issues in object detection are the shape variance, lighting variance and objects' pose variances.

II. Current Methods

Recent techniques for object detection are of two types: bottom-up approach and top down approach [3]. Top down approach includes a training stage to obtain class-specific model features or to define object configurations [1]. Bottom-up approach builds hypotheses from such features, extend them by construction rules and then evaluate by certain cost functions [2]. One of the current methods is to combine these two methods so that exhaustive searching and grouping can be avoided and the consistency in object hypotheses can be maintained.

III. Proposed Method

We developed a method by combining the bottom up approach with a graph based co-segmentation [5] of the image where the background may contain same type of objects. First we build groups of image classes for a training set, and then from the test image we search for the object after partitioning the image using a graph partitioning algorithm. The following steps are discussed below.

A. Image class preparation

For each object class we prepared a set of characteristics from sample images where the objects are segmented manually. Each entry is defined by the set $d_i = (h_i, e_i, p_i)$ where h_i is the histogram of the image, e_i is the edge matrix of the image and p_i is the mean variation of the contrast inside the edge boundary of the object.

B. Segmentation of the same type of object from background

Here we took two images for segmentation one having the object used in the class preparation and another having n number of overlapping objects. We used Maximum Ownership Labeling [4] to mark the desired object and we stored the weight matrix difference as a parameter for the graph partitioning.

The segment label c(x) = k for a pixel x is the k which maximizes the ownership of F(x) in the MoG model M. That is

$$c(\vec{x}) = \arg\max_k \left[\frac{\pi_k g(\vec{F}(\vec{x}) \mid \vec{m}_k, \Sigma_k)}{p(\vec{F}(\vec{x}) \mid M)} \right]$$

Where MoG is the Mixture of Gaussians Model and is defined by

$$p(\vec{F}|M) = \sum_{k=1}^{K} \pi_k g(\vec{F} \mid \vec{m}_k, \Sigma_k)$$

F(x) is the feature vector.

Here $\pi_k \geq 0$ are the mixing coefficients, with $\sum_{k=1}^{K} \pi_k = 1$, a
Σ_k are the means and covariances of the component Gaussians.

For a given K, the parameters $\{(\pi_k, \vec{m}_k, \Sigma_k)\}_{k=1}^{K}$ of the MoG can be fit to the data $\{\vec{F}(\vec{x})\}_{\vec{x}\in X}$ using maximum-likelihood (denotes the set of all pixels).

C. Graph Construction

We take a Graph based approach to segmentation.

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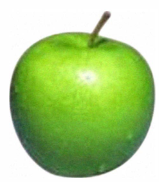
Let G = (V, E) be an undirected graph with vertices $v_i \in V$, the set of elements to be segmented, edges $(v_i; v_j) \in E$ corresponding to pairs of neighboring vertices. Each edge $(v_i; v_j) \in E$ has a corresponding weight $w((v_i; v_j))$, which is a non-negative measure of the dissimilarity between neighboring elements v_i and v_j. A segmentation S is a partition of V into components such that each component $C \in S$ corresponds to a connected component in a graph G' = (V, E'), where $E' \subseteq E$. This means that edges between two vertices in the same component should have relatively low weights, and edges between vertices in different components should have higher weights.

IV. Testing

For our experiments we first train the system using the following images.

(a)



(b)

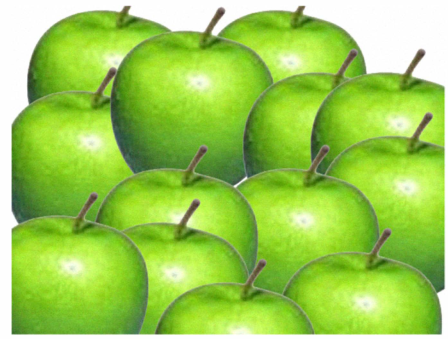
(c)

(d)

Figure 1. Image used for training (a) Red Apple (b) Green Apple (c) Designed Brown Button and (d) White Button with holes inside

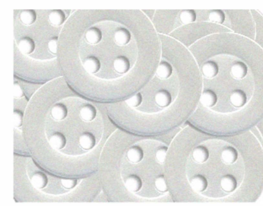
After class preparation from the figure, we had four classes of objects. Then we used the segmentation algorithm to partition different class of objects from the following images. In Fig 2. (a) We have background having same type of objects here we mapped every object and stored the feature vector F(x).

In Fig 2.(d) we have some of the white button above the brown button. After segmentation we marked the white buttons shown in Fig 2. (e). we stored the feature vector F(x) for the white button class from the image.



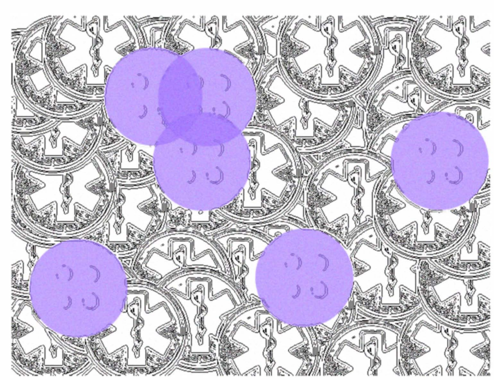
(a)

(b)



(c)

(d)



(e)

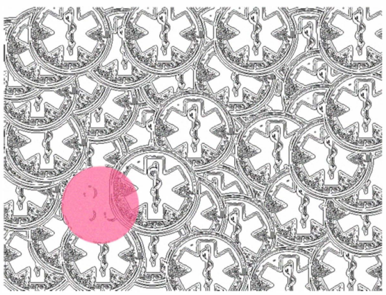
Figure 2. Images used for segmentation (a),(b),(c) represents same overlapping objects. (e) is the marked white button from (d)

V. Object Identification

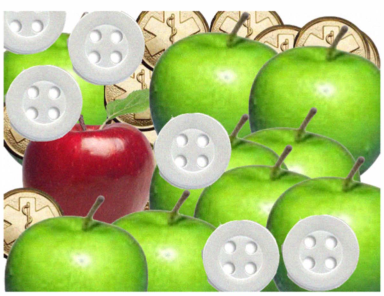
After training the system we combined all four classes of objects and we search for a particular class of object.

In Fig 3. (a) We searched for the white button and in Fig 3. (c) we searched for the red apple from the chaotic background.

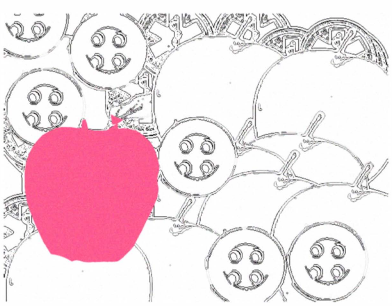
(a)



(b)



(c)



(d)

Figure 3. Successful prediction of (b) white button and (d) Red Apple

We trained and used our method to detect several objects from nature. The test results are given in Table 1.

TABLE I. Experimental Data

Objects	**Training and Identification Data**		
	No. of Training using different images	***Avg. no of different Objects in Background***	***Percentage of Successful Identification***
Button	10	100	100
Button	10	1000	89.47
Apple	15	1000	92.71
Flower	10	1000	79
Human	15	30	95.77
Human	20	50	96.11

VI. Conclusion

In this paper, we discussed about a graph based Image Segmentation and object identification method, especially where the background is chaotic and contains several same type of object. Our method successfully identified the search object from the chaotic background. However the method lacks its identification where the object seems multipart such as human body.

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