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Extraction of Foreground objects from Common Related Group of Images by Co-Segmentation Algorithm using LE and HE optimization

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ABSTRACT

A novel interactive image co-segmentation algorithm using likelihood estimation and higher order energy optimization is proposed for extracting common foreground objects from a group of related images. Our approach introduces the higher order clique's, energy into the co-segmentation optimization process successfully. A region-based likelihood estimation procedure is first performed to provide the prior knowledge for our higher order energy function. Then, a new co-segmentation energy function using higher order cliques is developed, which can efficiently co-segment the foreground objects with large appearance variations from a group of images in complex scenes. Both the quantitative and qualitative experimental results on representative datasets demonstrate that the accuracy of our co-segmentation results is much higher than the state-of-the-art co-segmentation methods.

Keywords: Discrete crack formation, service loads, flexural cracks, Epoxy resins, retrofitting techniques

I.INTRODUCTION

Cosegmentation automatically extracts common objects from multiple images by forcing the segments to be consistent, which can be used in many applications, such as image classification , image retrieval and object recognition . Such a task is extremely challenging when dealing with large variations of common objects and the interferences of complex backgrounds.

In the past several years, many co-segmentation methods have been proposed, which usually add foreground consistency constraint into traditional segmentation models to achieve the common object extraction, such as graph cut based co-segmentation, random walker based co-segmentation , active contours based co-segmentation , discriminative clustering based co-segmentation , and heat diffusion based co-segmentation Co-segmentation scenarios To the best of our knowledge, the task of co-segmentation has not previously been clearly defined. We argue that there is no "generic" co-segmentation problem.

Indeed, "similarly looking object" can refer to different scenarios and each will have different degrees of variability of object appearances; co-segmentation algorithms should ideally take this into account. In some previous work, "similarly looking object" referred to objects of the same class and the task was called unsupervised class segmentation (we discuss this in more detail in the next section).

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Cosegmentation can also refer to the case where the images depict the same physical object. This scenario can be very challenging if, for example, the images capture different physical parts of the object (viewpoint or zoom change) or the object is deformable. Examples of such variations are the Stonehenge, Statue and Alaskan bear classes . In fact, we believe that this may be even more challenging than segmenting different object instances from the same class, e.g. different spoons.

II. INTRODUCTION TO IMAGE PROCESSING

Pictures are the most common and convenient means of conveying or transmitting information. A picture is worth a thousand words. Pictures concisely convey information about positions, sizes and inter relationships between objects. They portray spatial information that we can recognize as objects.

Human beings are good at deriving information from such images, because of our innate visual and mental abilities. About 75% of the information received by human is in pictorial form.

In the present context, the analysis of pictures that employ an overhead perspective, including the radiation not visible to human eye are considered. Thus our discussion will be focussing on analysis of remotely sensed images. These images are represented in digital form. When represented as numbers, brightness can be added, subtracted, multiplied, divided and, in general, subjected to statistical manipulations that are not possible if an image is presented only as a photograph.Although digital analysis of remotely sensed data dates from the early days of remote sensing, the launch of the first Landsat earth observation satellite in 1972 began an era of increasing interest in machine processing (Cambell, 1996 and Jensen, 1996).Previously, digital remote sensing data could be analyzed only at specialized remote sensing laboratories.

Specialized equipment and trained personnel necessary to conduct routine machine analysis of data were not widely available, in part because of limited availability of digital remote sensing data and a lack of appreciation of their qualities.

III. COLOUR IMAGE PROCESSING

In particular this material is used in this book image data compression and for pyramidal representation in which images sub-divided successively into smaller regions.

The following terms are used to define colour light:
1. Brightness or Luminance: This is the amount of light received by the eye regardless of colour.
2. Hue: This is the predominant spectral colour in the light.
3. Saturation: This indicates the spectral purity of the colour in the light.

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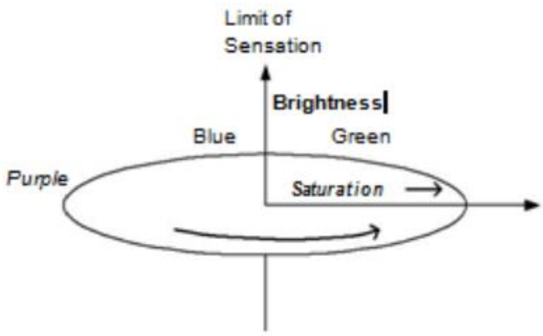

Figure 1 : Shows Colour Attributes

IV. INTRODUCTION TO IMAGE SEGMENTATION

Image segmentation is the division of an image into regions or categories, which correspond to different objects or parts of objects. Every pixel in an image is allocated to one of a number of these categories.A good segmentation is typically one in which:[2] pixels in the same category have similar grey scale of multivariate values and form a connected region, neigh blundering pixels which are in deferent categories have dissimilar values. For example, in the muscle image, each cross-sectional could be viewed as a distinct object, and a successful segmentation would form a separate group of pixels corresponding to each.

Similarly in the SAR image, each could be regarded as a separate category. Segmentation is often the critical step in image analysis: the point at which we move from considering each pixel as a unit of observation to working with objects (or parts of objects) in the image, composed of many pixels. If segmentation is done well then all other stages in image analysis are made simpler. But, as we shall see, success is often only partial when automatic segmentation algorithms are used. However, manual intervention can usually overcome these problems, and by this stage the computer should already have done most of the work.. After segmentation, methods of mathematical morphology can be used to improve the results. The segmentation results will be used to extract quantitative information from the images. There are three general approaches to segmentation, termed thresholding, edge-based methods and region-based methods.

V. PROPOSED METHOD

MAXIMUM LIKELIHOOD ESTIMATION (MLE) :

In statistics, maximum likelihood estimation (MLE) is a method of estimating the parameters of a statistical model given observations, by finding the parameter values that maximize the likelihood of making the observations given the parameters. MLE can be seen as a special case of the maximum a posteriori estimation (MAP) that assumes a uniform prior of the parameters, or as a variant of the MAP that ignores the prior and which therefore is un-regularized. Our co-segmentation procedure includes two main steps. The first step is a fast but effective likelihood estimation process, which calculates the probabilities of pixels belonging to fore-ground/background over entire dataset according to user scribbles. The estimated likelihood offers a rough estimation for foreground /background and is fed into next step as prior

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knowledge. In the second stage, a higher-order energy based co-segmentation function is proposed to obtain final accurate co-segmentation results on a group of images, which is based on higher order cliques. Our higher-order cliques are constructed from a set of foreground and background regions by user scribbles, where all the regions in each image are matched to produce better co-segmentation performance. Additionally, our approach considers the quality of segmentation in higher-order energy to obtain more accurate estimations of foreground/background.

The method of maximum likelihood is used with a wide range of statistical analyses. As an example, suppose that we are interested in the heights of adult female penguins, but are unable to measure the height of every penguin in a population (due to cost or time constraints). Assuming that the heights are with some unknown mean and variance, the mean and variance can be estimated with MLE while only knowing the heights of some sample of the overall population. MLE would accomplish that by taking the mean and variance as parameters and finding particular parametric values that make the observed results the most probable given the normal model.

HIGHER ORDER IMAGE COSEGMENTATION

Via our likelihood estimation, we have a fast and rough estimate for foreground/background in each image. For generating more accurate co-segmentation results, we further propose a higher-order energy based co-segmentation function. In order to simultaneously segment a group of input images {I1, . . . , In} with the labeled images T, we first build a global term Eglobal(I1, . . . , In, T) to match all the images with the labeled images T. The proposed energy of our co-segmentation algorithm is expressed as follows:

$$\mathcal{F} = \sum_{i=1}^{n} \left(\epsilon_1^i E_{\text{unary}}^i + \epsilon_2^i E_{\text{pairwise}}^i \right) + E_{\text{global}}(I^1, \ldots, I^n, T)$$

Higher-order energy function utilizes clique likelihood for foreground and background. The region consistency in our higher-order clique is also taken into account as an evaluation for segmentation quantity. In other words, our higher-order energy function considers the similarity between higher-order clique and foreground/background, which encourages all the pixels of a region to take the same label. Next we will introduce our optimization method for higher-order energy. Because the value of is constant, the problem of minimizing our higher-order energy function can be transformed into a problem of minimizing the matching coefficient, which is defined in the following two important theorems**.**

VII. RESULTS AND DISCUSSION

Improvement for our method through higher-order Co-Segmentation results are (a) The input images; (b) the map of likelihood estimation (in this map, the more white colors that a region has, the higher possibility that the region belongs to foreground); (c) cosegmentation results by our likelihood estimation; (d) co-segmentation results by our method without higher-order cliques energy, which means we only use the unary item and pairwise item without higher-order item of (9); (e) co-segmentation results by our full method with higher-order energy optimization; and (f) the ground truth masks.

The experimental results demonstrated both qualitatively and quantitatively that our method has achieved more accurate cosegmentation results than previous unsupervised and interactive co-segmentation methods, even though the foreground and background have many overlap regions in color distributions or in very complex scenes.

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Figure 2: Shows Co-Segmentation Algorithm using LE and HE optimization

We have presented a novel interactive co-segmentation approach using the likelihood estimation and high-order energy optimization to extract the complicated foreground objects from a group of related images. A likelihood estimation method is developed to compute the prior knowledge for our higher-order co-segmentation energy function. Our higher-order cliques are built on a set of foreground and background regions obtained by likelihood estimation. Then our co-segmentation process from a group of images is performed at the region level through our higher-order cliques energy optimization. The energy function of our higherorder cliques can be further transformed into a second-order boolean function and thus the traditional graph cuts method can be used to solve them exactly.

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