Bi-modal Image Segmentation by Active Shape Model

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Abstract— **This paper deals with Bi-modal Image segmentation with active shape model. This method has been applied to varieties of segmentation problems, where considerable information about the shape is available. The discussion about the implementation on a set of both synthetic and natural bimodal images is presented.**

Keywords— Image segmentation, Bimodal image, Active Shape models, Computer Vision

I. INTRODUCTION

Image segmentation is a crucial step in the interpretation of image. The extraction of information from an image is guided by the accuracy of segmentation, which is a problem far from solved. Conventionally, inspection by a human observer is performed, in a production line of a factory or in diagnostics. If this trained operator is to be replaced by a real-time system intended for detection and hence classification of objects of interest in a given image, resulting in increased productivity, then an elaborate segmentation algorithm will be needed. The aim of image segmentation is to divide the image in to meaningful sections. Thresholding, edge based segmentation and region based segmentation are the important groups of segmentation methods. A better segmentation result is obtained if more *priori* knowledge is available to the entire process.

The application areas vary from industrial to medical fields, each having a specific requirement of segmenting the region of interest like machine vision, object detection, biometrics, traffic and surveillance system etc. to name a few.

II. PREVIOUS WORK

The work done on image segmentation has been to address a particular problem in one domain, like segmenting the ventricles of the heart. Depending on the imaging modality, task at hand etc, various algorithms have been developed and validated. There are various data bases for cross validation of one's algorithm. Some of the early segmentation techniques, well suited for majority of imaging techniques are:

A. Histogram

A simple thresholding of the image results in non-object pixels also to be segmented as otherwise, as shown in Fig.1. As a starting point, our image data set consists of bimodal images, giving scope for implementing histogram based segmentation algorithm. The algorithm of Ridler [1] et al works well in multimodal cases also. But as the contents of the image increase, these methods will have erroneous segmentation. The start of peak in the histogram, its end etc have been used for the data reduction by Sezan [2].

B. The Snakes

The locations of boundaries are to be defined by gradients which will be detected by the evolving curve, called snakes or active contour models, if an approximate shape of the contour is already known, Kass et al [3].

C. Other methods in literature

The Hough transform has been used to detect shapes in the images even in cases of broken edges and noise by Ding et al [4]. Gados and Horvath [5] describe a technique based on heuristics and a set of rules for segmentation, which could find the lungs' edges on an x-ray image, which is always superimposed with that of the heart. There are many such different methods each of which exploiting a particular feature for segmentation [6, 7].

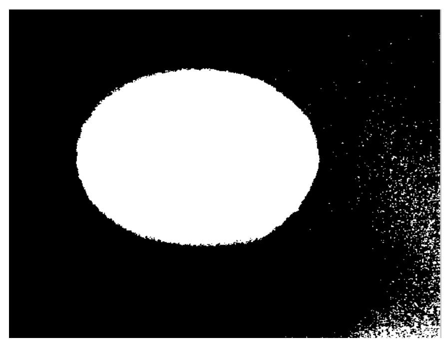

Fig. 1. A binary image created by thresholding an image from our data set.

The model based method is a solution to the task of segmentation in cases where the object can be modeled. T.F. Cootes [8] et al presented a statistics based technique for building compact shape model for any flexible object, which we have tried to implement and evaluate for both real and synthetic images. The method, known as Active Shape Model (ASM), has been applied in various fields of image segmentation tasks, whose steps are repeated here succinctly.

III. ACTIVE SHAPE MODEL: SEGMENTING SHAPES

The model building starts with a set of images, each having the example of structure we wish to model. This developed

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model will then be used to interpret the images. The images containing the shapes will have to be marked for the salient points such as edges or corners of the objects etc., by a set of points. The points are labeled manually by locating the shape visually on each image ensuring there are no deviations from one image to another image, since each point represents a salient part of the structure. Each of the **N** images will have the same ***n*** points, and training set can have as many variations in structure as possible.

Considering $\mathbf{x_i} = (x_{i0}\ y_{i0},\ x_{i1}\ y_{i1},\ldots\ x_{in-1}\ y_{in-1})$ to describe the **n** labeled points of the $\mathbf{i}^{th}$ shape in the training set, where (x_{ij}, y_{ij}) is the $\mathbf{j}^{th}$ point of $\mathbf{i}^{th}$ shape. These points are marked on all the N training shapes, and the mean shape $\bar{\boldsymbol{x}}$ is calculated using

$$\bar{\mathbf{x}} = \frac{\mathbf{1}}{\mathbf{N}}\sum_{\mathbf{i=1}}^{\mathbf{N}}\mathbf{x_i} \quad (1)$$

These points are carefully marked, and all correspond to a same point on the shape. Each set of points on a given shape vary from the mean $\bar{\boldsymbol{x}}$**.** These deviations which are called modes of variation are determined by applying Principal Component Analysis (PCA), which is a common technique of finding patterns in high dimensional data. The deviations of every shape from the $\bar{\boldsymbol{x}}$ are given by

$$\mathbf{dx_i} = \mathbf{x_i} - \bar{\mathbf{x}} \quad (2)$$

To determine the modes of variations of all the labeled points on the shape, we find the unit Eigen vectors of the covariance matrix S, given by

$$\mathbf{S} = \frac{\mathbf{1}}{\mathbf{N}}\sum_{\mathbf{i=1}}^{\mathbf{N}}\mathbf{dx_i dx_i^T} \quad (3)$$

of size 2n x 2n. It will have 2n Eigen values, out of which the significant modes of variation in the variables are described by the set of largest Eigen values of **S**. The concept of dimensionality reduction is to choose a set of small number of largest Eigen values. We have chosen a set which accounted for almost 97% of the variance in the data. With a combination of the Eigen vectors of the largest Eigen values retained and a variation of them with the mean shape, almost any shape from the set of training shapes can be approximated as

$$\mathbf{x} = \bar{\mathbf{x}} + \mathbf{Pb} \quad (4)$$

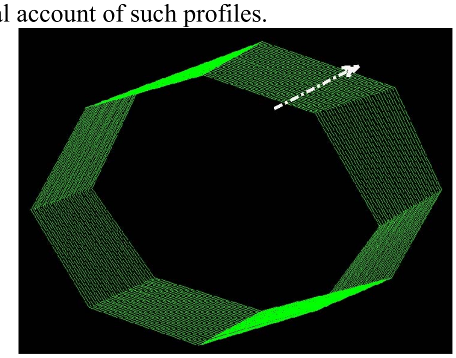
where, **P** is the matrix of eigenvectors corresponding to the largest Eigen values and **b** is a vector of weights. By varying the vector **b**, which is basically Eigen values, in a suitable limit, it is possible to generate a new training set. Figure 2 shows the shapes generated by varying first and second largest Eigen values. The superimposed arrows show the direction of variation.

A. Modeling the Gray level at each landmark point

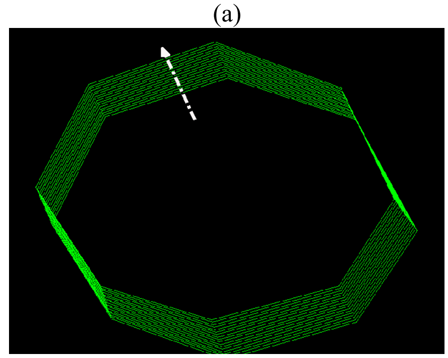
After capturing the shape model from the training set, it is important to model the gray level of the pixels around the label points. Each point labeled, either manually or automatically, is a salient feature of the shape, like a corner, edge or such other identifiable feature. The information about each ***i*** labeled points from every image ***j*** is to be captured in the form of a model, so as to search them in the test image. Earlier works have shown that incorporating the gray level model at each point will improve the searching of the location of the points. The region around the labeled point is to be represented in a one-dimensional array of gray levels of certain pixel length say $\mathbf{n_p}$, which we have taken as 15 for a 500X500 pixels image and 42 for 1600X1200 pixels image. This gray level model $\mathbf{g_{ij}}$ centered at the model point, is obtained for every **i** points from each image **j**. This model should then be normalized to obtain invariance to the addition of a constant or uniform scaling of gray levels. Then a mean profile is evaluated for each point **i** as,

$$\bar{g}_i = \frac{1}{N}\sum_{j=1}^{N} g'_{ij} \quad (5)$$

A $\mathbf{n_p}$ **x** $\mathbf{n_p}$ covariance matrix can be calculated pointing to the statistical account of such profiles.



(a)



(b)

Fig 2. A set of shapes generated by varying the Eigen values in equation 4. The arrow indicates the direction of variation. (a) shapes obtained by varying largest Eigen value (b) shapes obtained by varying second largest Eigen value

IV. DATA AND METHOD

In this implementation of the ASM based algorithm, we have used both synthetic and natural images. We have 45 synthetic images each of the size 500 X 500 pixels where as 60 natural images, typically of the size 1600 X 1200 pixels. The natural images were obtained with an ordinary 2.1 mega pixel cell phone camera of an elliptical object, without flash. The orientations of elliptical shape in each of the training images were kept same as an initial assumption. The position and scale of the shape is different in each image. A few images from the training set are shown in Fig. 3. The first row shows synthetic images of size 500 X 500 pixels. The second and third rows show natural images of an elliptical object. The elliptical object was chosen such that the background and object together give rise to a bimodal image.

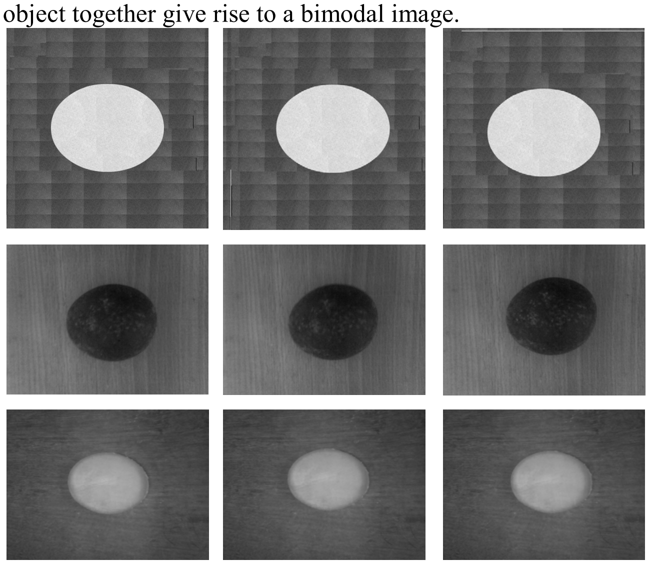


Fig 3: A set of images used for training the ASM segmentation algorithm

The search process involves finding an instance of the modeled shape, if present in the given image. Further in order to locate the shape iterative steps are defined, in which the deformable shape fits to similar object in the surrounding. In our effort of implementing this, as an initial step, we have retained elliptical shape in our test images and only scale and positions are changed. The initial placement of the model will guide the subsequent search of the image. Here we have taken the average location of all the training shapes as the location to place the model initially. Then, at the corresponding points a gray level model is derived, of length 120. For the shapes that we have assumed, this length makes it possible to look for a suitable point in a longer range. The numbers of labeled points in our example have been in the range of 8 to 32. Each of these model points' locations are shifted to a fitting new location. This new location is found by correlating the model gray level profile for that point **i** with gray level available in the image along the normal to the edge of the shape.

V. RESULTS AND DISCUSSION

ASM has been applied in detecting the shapes where the model profiles are (i) distinct edges, having a very clear demarcation between object and surrounding and (ii) blur edges. It was observed that irrespective of the boundary type, the ASM based algorithm is able to detect it. The model point profiles are shown as red/asterisk curve in Fig. 5(a) for a distinct or strong edge, where the profile is clearly dividing the object and background region. Fig. 5(b) and 5(c) show the model profile for blur edges. As can be seen in these profiles, the object and background are not having distinct features. Each corresponds to a typical image from the each row of Fig.3.

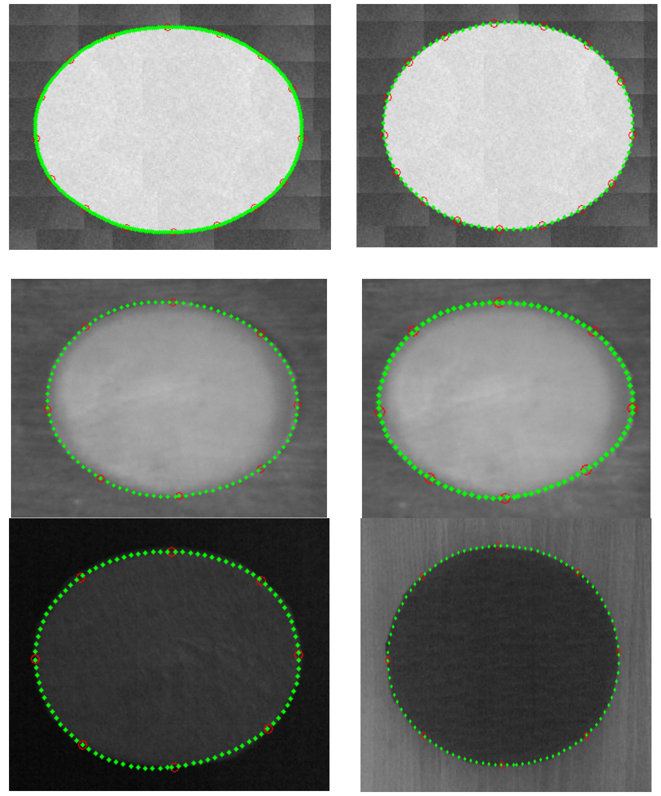
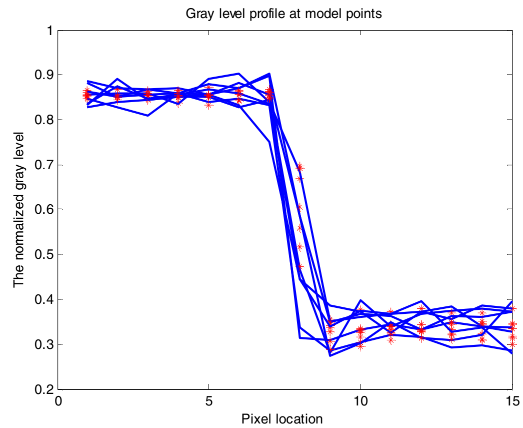


Fig. 4 A collection of images with the detected elliptical shape. The first row is of synthetic images and others are natural images.

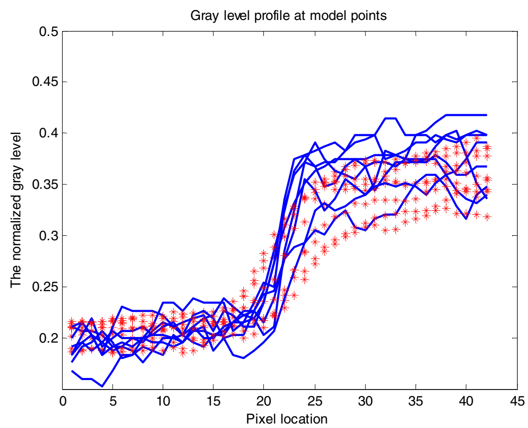
For a distinct edge shape, the task is reduced to finding the strongest boundary, as shown in Fig. 5(a), where difference between the object and background is large. But in Fig. 5(b) and 5(c), the profiles are not having a distinct profile at edges, which demands other local assumptions to correctly delineate the edge of the detected shape. Different profile models were tried on these set of images, each profile being built using 8, 10, 16 or 30 salient points. Computational time and memory requirement increase with the number of profile points. We have attempted to reduce the profile points and interpolate the same at different iterations, so that the detection progresses from coarse to fine. This way, total time required for the detection can be reduced.

A. Detection of the Shape

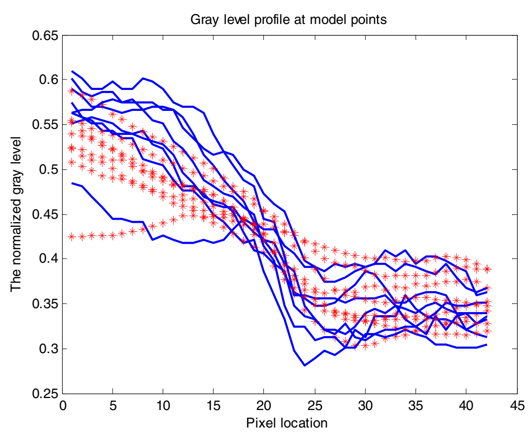
The algorithm was applied to the test image and we were able to detect the ellipse on the test images. Some examples of the images where accurate shape detection has been done is shown in Fig. 4. The array includes samples from each category of images shown in Fig. 3. To highlight the shape detection, we have cropped the image to retain only the detected shape. The time taken for each iteration for 500 X 500 pixel image was less than a second and for the rest it was 1.5 to 2 seconds, in MATLAB implementation.



(a)



(b)

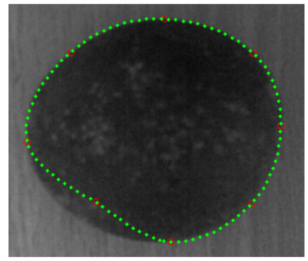


(c)

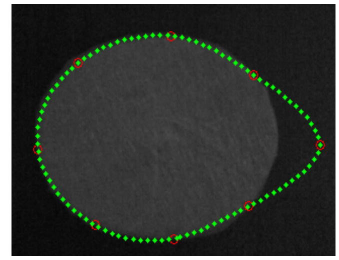
Fig 5. The red/asterisk curves are the model gray level profile at labeled points in training image set. The blues curves are the matching profiles found along the normal to the boundary in the test image.

B. *Incorrect Edge detection*

Fig. 6 (a) and (b) shows some instances where the detection of the edges has gone wrong mainly because of the noise. Once the algorithm deviates from the actual points or edge, it is difficult to correctly detect the edges. The algorithm can be run for a preset number of iterations or until there is no significant change in the results, from one iteration to the other.



(a)



(b)

Fig. 6 (a) & (b) Occasional incorrect boundary detection because of the presence of a pattern similar to boundary, which we have attributed the cause to the wrong modeling.

VI. CONCLUSION

The algorithm for modeling the shapes and its application to an image results in faithful segmentation depending on the accuracy of the model. It is necessary to have all possible instances of the shapes during training phase to build a deformable model. The ASM based method has low runtime, and hence can be implemented for real time applications too.

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