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Understanding Active Shape Model

Arvind B[1], Kiran Noolvi[2], Nithin Kumar H M[3], Shreyas K Bhat[4], Prashanth A Athavale[5,6]

Abstract: Active shape models (ASMs) are statistical models of the shape of objects which iteratively deform to fit to an example- of the object in a new image, developed by Tim Cootes and Chris-Taylor in 1995. The technique determines the statistics of the points over a collection of example shapes. The mean positions of the points give an average shape and a number of modes of variation are determined describing the main ways in which the example shapes tend to deform from the average. In this way allowed variation in shape can be included in the model. The method produces a compact flexible 'Point Distribution Model' with a small number of linearly independent parameter, which can be used during image search.

Keywords: statistical model, Point distribution model, Image segmentation, Image Processing.

I. INTRODUCTION

Image segmentation is the process of partitioning a digital image into multiple segments(sets of pixels also known as super pixels). The goal of segmentation is to simplify or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics.

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. Each of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Image segmentation is one of the fundamental requirements in image analysis[1].

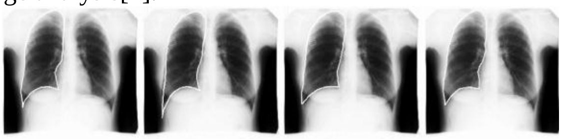

Fig1.Example result for the right lung field segmentation

The techniques for image segmentation roughly fall into two general processes:

1)Edge detection and line following: This category of techniques studies various of operators applied to raw images, which yield primitive edge elements, followed by a concatenating procedure to make a coherent one dimensional feature from many local edge elements. It is a process of locating an edge of an image[1]. When image edges are detected, every kind of redundancy present in the image is removed. There are many methods of detecting edges;

The majority of different methods may be grouped into these two categories:

a) **Gradient**: The gradient method detects the edges by looking for the maximum and minimum in the first derivative of the image.

b) **Laplacian**: The Laplacian method searches for zero crossings in the second derivative of the image to find edges.

2) Region based methods: Region based methods[1] depend on pixel statistics over localized areas of the image. Regions of an image segmentation should be uniform and homogeneous with respect to some characteristics such as grey tone or texture.

Algorithms used for segmentation are as follows:

1. Active Shape Model
2. Active Appearance Model

There are three key differences between the two algorithms:

1) The ASM only uses models of the image texture in small regions about each landmark point, whereas the Active Appearance Model(AAM) uses a model of the appearance of the whole of the region (usually inside a convex hull around the points)[2,3,4].
2) The ASM searches around the current position, typically along profiles normal to the boundary, whereas the **AAM** only samples the image under the current position.
3) The ASM essentially seeks to minimize the distance between model points and the corresponding points found in the image, whereas the AAM seeks to minimize the difference between the synthesized model image and the target image

II. ACTIVE SHAPE MODEL SEGMENTATION

Goals of ASM:

- Searches images for represented structures
- Classify shapes Specific to ranges of variation
- Robust (noisy, cluttered, and occluded image)
- Deform to characteristics of the class represented
- "Learn" specific patterns of variability from a training set
- Utilize iterative refinement algorithm
- Apply global shape constraints
- Uncorrelated shape parameters
- Better test for dependence

*: Students of 8th semester Electrical & Electronics Engineering
**:Professor, Department Of Electrical & Electronics, BMSIT

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As van Ginneken et al[5] pointed out that segmentation can generally be approached from two sides. When taking the bottom-up approach the image structure is analyzed and described as a collection of low-level elements and their spatial relationship to each other. The top-down approaches try to build a high level model that describes the class of objects that should be identified in images and segmented correctly. Active Shape Models are **a top-down approach**. The model interprets points on the contour of the corresponding object as a point distribution. The goal is to capture the variations of the shape of the object class during training. The model is then used during fitting by displacing the points on the boundary of the model until they match the shape of the object in a given image. The general approach involved to generate and apply Active Shape Models as presented by Cootes et al. The general approach is to first **train the model** with a set of training images . The second step is to use this model during the fitting process for new images that we would like to segment.

III. TRAINING THE ACTIVE SHAPE MODEL

Initially we need a set of training images to construct the models. This is done by manually placing points on boundaries or features of the objects in the set of training images that we would like to recognize. After the points have been placed a number of representative points are chosen. Cootes et al[6] name three types of representative points or landmark points that can be chosen. The first type are application dependent points which means that they depend on the type of objects we would like to recognize. The second type are application independent points which as the name suggest do not depend on the type of objects that have to be picked out like curvature extrema along the boundaries of the shape defined by the placed points. The third type , landmark points are points that can be interpolated from the first two set of points.

After acquiring the set of landmark points we have to align the shapes from all training images in order to build a meaningful model. Once all shapes are aligned to a given shape we calculate the mean shape from the aligned shapes. Later we need to normalize the mean shape which means that we choose some default orientation, scale and origin. Finally we realign all shapes to the mean. We repeat this process of calculating the mean, normalization and realignment until convergence. The normalization is essential to ensure convergence, since otherwise we would not have any meaningful comparison measure of alignment. Van Ginneken et al. note that in some cases alignment is not desired and therefore omitted[7].

This can be if the shape of the objects only varies slightly within a given range. We need to align the shapes we want to derive a model that describes these shapes. This is done by statistically analyzing the set of given shapes. We can describe each shape by the coordinates of its landmark points. Assuming that the shapes consist of n landmark points each, we can describe each shape as a vector of n **2**-dim points. Furthermore, we can specify each shape to be a point in **2n**-dim space. Since the landmark points are partially correlated the points representing the shapes form a cluster in **2n**-dim space.

Cootes et al make the assumption that the points roughly approximate an high-dimensional ellipsoidal object. Following the assumption it is now possible to describe this cluster in terms of a center and major axes.

The center is simply the mean $\bar{\mathbf{x}}$. In order to capture the possible variations of the shape we calculate the deviation from the mean

$$\mathbf{dx_i} = \mathbf{x_i} - \bar{\mathbf{x}}$$

where $\mathbf{x_i}$ is the shape vector. The deviations allow us to build a covariance matrix

$$S = \frac{1}{k}\sum d\,x_i dx_i^T$$

where ‘k’ is the number of shapes extracted from training images**.**

The landmark points are (manually) determined in a set of s training images. From these collections of landmark points, a **point distribution model**[8] is constructed as follows. The landmark points $(x_1\ ,y_1)\dots\dots(x_n,y_n)$ are stacked in shape vectors

$$\mathbf{X}=(\mathbf{x_1}\ ,\mathbf{y_1}\dots\dots\mathbf{x_n},\mathbf{y_n})^{\mathbf{T}}$$

Principal component analysis (PCA) is applied to the shape Vectors **x** by computing the mean shape

$$\bar{\mathbf{X}}=\frac{1}{s}\sum_{i=1}^{s}\mathbf{X_i}$$

The covariance

$$\mathbf{S}=\frac{1}{s-1}\sum_{s-1}^{s}(\mathbf{X_i}-\bar{\mathbf{X}})\,(\mathbf{X_i}-\bar{\mathbf{X}})^{\mathbf{T}}$$

and the eigen system of the covariance matrix. The eigenvectors corresponding to the largest eigen values γ_i are retained in a matrix $\emptyset = (\emptyset_1|\emptyset_2|\dots.|\emptyset_t)$. A shape can now be approximated by

$$\mathbf{X}\approx\bar{\mathbf{X}}+\emptyset\mathbf{b}$$

where **b** is a vector of **t** elements containing the model parameters, computed by

$$\mathbf{b}=\emptyset^{\mathbf{T}}(\mathbf{X}\text{-}\bar{\mathbf{X}})$$

When fitting the model to a set of points, the values of **b** are constrained to lie within the range $\pm m\sqrt{\gamma_i}$, where **m** usually has a value between two and three.

The number **t** of Eigen values to retain is chosen so as to explain a certain proportion f_v of the variance in the training shapes, usually ranging from 90% to 99.5%. The desired number of modes is given by the smallest **t** for which

$$\sum_{i=1}^{t}\gamma_i \geq f_v\sum_{i=1}^{2n}\gamma_i$$

Before PCA is applied to the shapes, the shapes can be aligned by translating, rotating and scaling them so as to minimize the sum of squared distances between the landmark points.

An iterative scheme known as Procrustes analysis [9] is used to align the shapes for details see [10]

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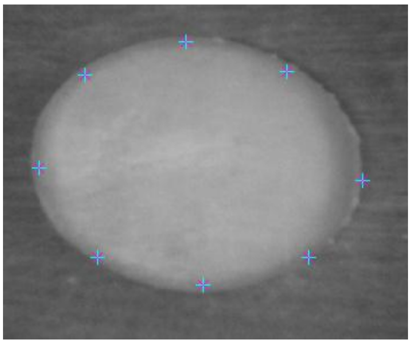


Fig2. Manually locating the landmark points in image(image 1)

IV. FITTING THE ACTIVE SHAPE MODEL

Assume that the shape we are searching for is visible in the image. Then we need to deform our ASM in such a way that it matches the shape. The boundary of the object we want to segment is given by the displaced landmark points of the ASM. While there are several methods and approaches to training and fitting the ASM we need an initial estimate of the position of the landmark points in the image. Once the points are placed, we then iteratively transform the landmark points. This transformation is repeated until the position of the landmark points does not change significantly anymore. By examining the image structure around the landmark points in question we can determine if we should continue displacing the points. Ideally this would result in landmark points that are placed on the boundary of the object in the image we are segmenting. This hugely depends on the quality of the model we have trained.

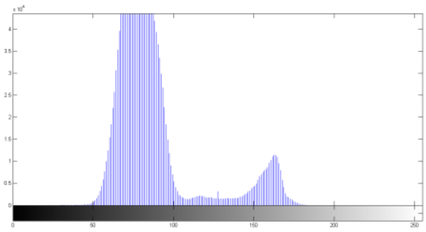


Fig3.Intensity variation in an image(image1)

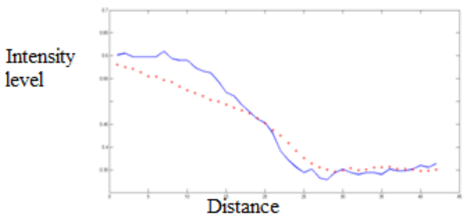


Fig4.Comparison between image under search and average model

V. GRAY-LEVEL APPEARANCE MODEL

The gray-level appearance model that describes the typical image structure around each landmark is obtained from pixel profiles, sampled (using linear interpolation) around each landmark, perpendicular to the contour. Note that this requires a notion of connectivity between the landmark points from which the perpendicular direction can be computed. By calculating the model from the training images we can then displace the landmark points of the mean model during the fitting process for a new image in such a way that the image structure around the transformed points is similar to those of the model.

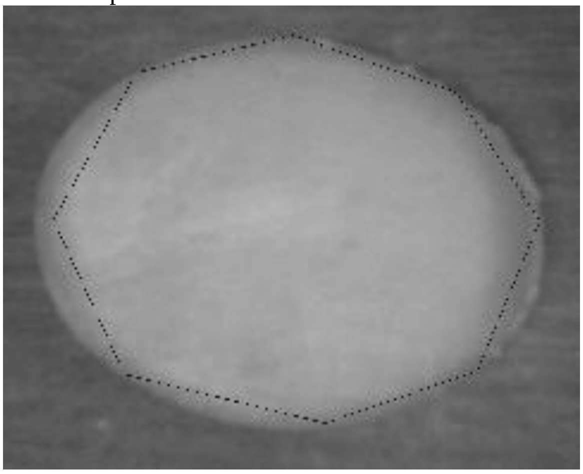
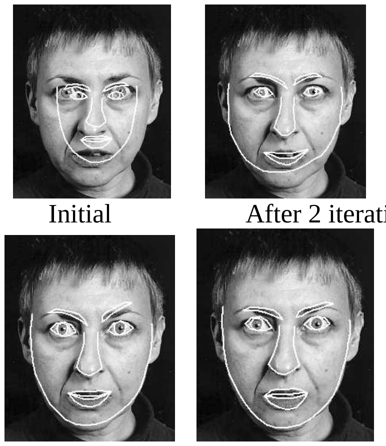


Fig5.Grey-level appearance model

Example of image search Figure 6 demonstrates using the ASM to locate the features of a face. The model instance is placed near the centre of the image and a coarse to fine search performed. The final convergence (after some 18 iterations) gives a good match to the target. The algorithm converges in much less than a second (on a 200MHz PC). See for details[11]



Initial After 2 iterations

After 6 iterations After 18 iterations

Fig6.Image 2

VI. APPLICATION

Active shape algorithms found application in

- Medical
- Industrial
- Surveillance
- Biometrics
- Agricultural etc

We demonstrate the method by applying it to problem of **locating the elliptical structure in a image**. These kind of images demonstrate a less degree of variation in both shape and texture.

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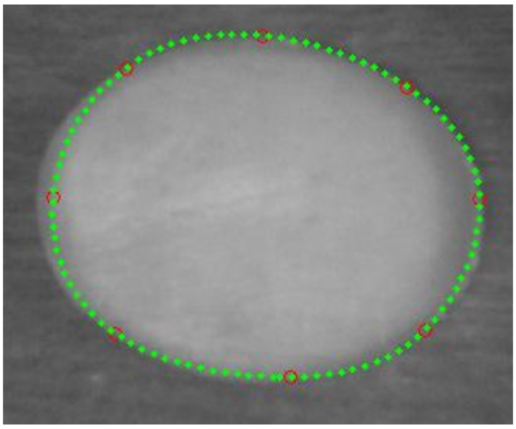

Fig7.Locating oval shape in a image

Locating features in images of the human face: Images of the face can demonstrate a wide degree of variation in both shape and texture. Appearance variations are caused by differences between individuals, the deformation of an individual face due to changes in expression and speaking, and variations in the lighting

Fig8.Example face image annotated with landmarks

Application in medical sciences such as locating the cartilage in MR images of a knee When analysing the MR images of the knee (see Fig9), we wish to accurately locate the boundary of the cartilage in order to estimate its thickness and volume [11]

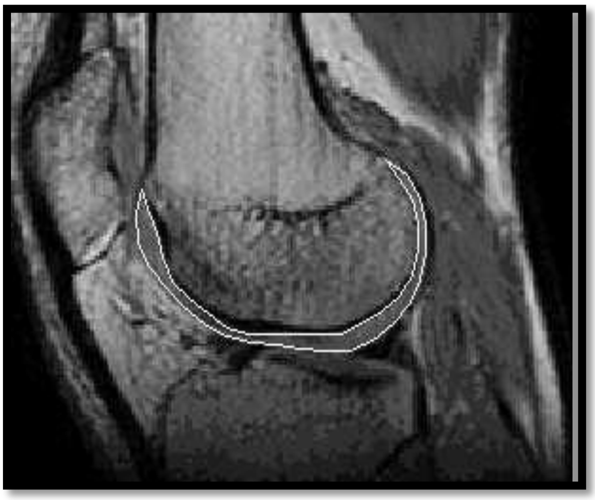

Fig9.Example MR image of knee with cartilage outlined

Some other medical applications are:
Detection of texture of iris of human eyes.
Detection of holes in human heart
Defects in Lung Nodules [12]

VII. CONCLUSION

Active Shape Models allow rapid location of the boundary of objects with similar shapes to those in a training set, assuming we know roughly where the object is in the image. They are particularly useful for:

- Objects with well defined shape (eg bones, organs, faces etc)
- Cases where we wish to classify objects by shape/appearance
- Cases where a representative set of examples is available
- Cases where we have a good guess as to where the target is in the image However, they are not necessarily appropriate for
- Objects with widely varying shapes (eg amorphous things, trees, long wiggly worms etc)
- Problems involving counting large numbers of small things

We have demonstrated ability to create a compact models of elliptical structure that can be successfully in image search

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