Combining Top Down Strategy With Bottom up Approach For Image Segmentation

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Abstract

Image segmentation is the problem of partitioning an image into its constituent components. In wisely choosing a partition that highlights the role and salient features of each component, we obtain a compact representation of an image in terms of its useful parts. In proposing an integrated approach for image segmentation based on a generative clustering model combined with coarse shape information and robust parameter estimation. The sensitivity of segmentation solution to image variations is measured by image resampling. Top down information & bottom up approach is combined into a semantic likelihood map in the framework of Bayesian statistics.

Keywords : Image segmentation, clustering, generalization, resampling, Bayesian statistics.

1. Introduction

The semantic abstraction from pixels to objects in computer vision requires grouping low-level information into coherent groups or segments. This segmentation stage in image interpretation is of prime importance in low and mid level vision. Since it substantially reduces the information about objects. According to Thomas Zolar and Joachim, M. Baumann [1], the segmentation process is implemented by a parametric distribution Clustering framework (PDC). PDC is combined with coarse shape information. Data groups are represented by continuous mixture models for color and texture feature distribution [1].

For any learning algorithm, the problems of robustness toward small fluctuations in the data as well as the generalization of inferred solution to previous unseen instances of dataset from the chosen domain are highly relevant. Image segmentation as a learning problem requires inferring a robust partitioning of image patches with generalization to novel images of the same type. In PDC a mixture model approach to segmentation with top down information is used [2]. PDC is an integrated approach for image segmentation based on generative clustering model combined with top down information (shape information and robust parameter estimation). The sensitivity of segmentation solutions to image variation is measured by image resampling. Shape and similarity based grouping information is combined into a semantic likelihood map in the framework of Bayesian Statistics [1].

Image segmentation is the problem of partitioning an image into its constituent components. In wisely choosing a partition that highlights the role and salient features of each component, we obtain a compact representation of an image in terms of its useful parts. A major goal of image segmentation is to identify structures in the image that are likely corresponding to scene objects. As proposed by Rousson and N. Paragios [15], current

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approaches to segmentation mainly rely on image based criteria such as grey level of image regions as well as smoothness and continuity of bounding contours or a combination of these [14]. The region based approaches recursively merge similar regions. "Divide-conquer" approaches recursively split regions into distinct sub regions. Contour based approaches emphasize the properties of region boundaries, such as continuity, curvature, smoothness and shape.

Boundary extraction is an important procedure for segmentation and pattern identification purposes in digital images, not only recognition and interpretation tasks, but also for object classification. The gradient operator is a widespread tool used for these purposes, detecting local level variations that could correspond to contours of interests.

Automated segmentation of images has been considered an important intermediate processing task to extract semantic meaning from pixels. In PDC continuous mixture models for color and texture feature distributions represent framework data groups where as individual image sites are characterized by feature measurements. PDC belongs to the clustering methods that share the property that they grow pixels or small image patches based on some measure of homogeneity of the associated features or of connectors in feature space. PDC approach is based on a generative model for the measured features. The observations at a given site are assumed to be generated by a particular Gaussian mixture model which is characteristics for the cluster.

1.1 Motivation

1. Implementation of Parametric Distributional Clustering Model

In order to characterize a clustering procedure the modeler has to specify the objects, which are to be, clustered, the nature of the features associated with these objects and the criteria on which the grouping is based. PDC segmentation method characterizes image parts by mixture of Gaussians, which define prototypical distributions for the measured features. Using an Expectation Maximization (EM) algorithm performs parametric distributional clustering.

2. Representation of Shape Knowledge

a. Segment the representative image of the object in a sketchy way.

b. The distances of every pixel in a given image to the now centered region depicting the object of interest are computed for the image by applying chamfer transform.

c. Apply the Gaussian probability function to this single image.

3. Semantic Likelihood Maps

The goal of our approach to shape driven image portioning is to utilize shape constraints in order to satisfactorily segment images, which contain objects of a certain semantic category.

- Key issue concerning successful application of shape constraints in a segmentation procedure is given by automatically identifying those regions in an input image which are likely to depict an object of the semantic category in which one is interested.

- Key idea for this is to utilize Gaussian mixture distributions in order to discern image regions depicting the object of interest from those, which merely display background clutter.

4. Bootstrap Sampling

Re sampling techniques can be used to generate multiple instances of the available data. Resampling approach provides a viable means of finding the most pronounced and presumably, the semantically important boundaries between image regions.

5. Combining Shape and Segmentation

The images are based on shape constrained segmentation come from the Corel image database [9] and Berkeley Segmentation Data Set.

Shape Constrained Segmentation

In shape-constrained image segmentation, shape constraints are obtained by applying chamfering technique (DT), interpreted as prior and denoted by Ps. and the posterior probability of the foreground semantic category denoted by Pwf. Both can be combined together to arrive get shape constrained image segmentation.

Probability assessment for the semantic categories into segmentation for the input image, each image site is assigned a label according to the maximum of posterior probability values for the foreground and background respectively. After computing label, one sweep of post processing step has been applied to the segmentation in which each site is relabeled. Another post processing step is applied in which all regions with area below the aforementioned threshold are eliminated.

2. Research Work

Empirical Study

The experiments were conducted with real world datasets, where true natural clusters are known, to validate both accuracy and robustness of consensus via mixture model. We explored the datasets using Berkeley database.

In this contribution, we present a Clustering approach based on parametric distributions that are generated from Gaussian mixture model, called Parametric Distributional Clustering approach (PDC). PDC is presented as a novel approach to image segmentation. The segmentation technique is formulated as a generative model in the maximum likelihood framework. The specific choice of clustering algorithm, is dependant on the nature of the given image primitives which might be feature vectors, feature relations. Or feature histograms. We suggest replacing non-parametric density estimation via histograms by a continuous mixture model.

2.1 EM Algorithm

The EM algorithm estimates the parameters of a model iteratively, starting from some initial guess. Each iteration consists of an expectation step, which finds the distribution for the unobserved variables, given the known values for the observed variables& the current estimate of the parameters. Maximization step, re estimates to be those with maximum likelihood, under the assumption that the distribution found in the E step is correct. Once a model is specified with its parameters, and data have been collected, one is in a position to evaluate its goodness of fit, i.e., how well it fits the observed data. Goodness of fit is assessed by finding parameter values of a model that best fits the data- a procedure called "Parameter estimation".

2.2 Hierarchical Chamfer Matching For Shape Alignment

Matching is a key problem in digital image analysis and edges are perhaps the most important low-level image features [5]. Thus good edge matching algorithms are important. The paper edited by Borgefors presents such an algorithm, the hierarchical chamfer-matching algorithm. The al-gorithm matches edges by minimizing a generalized distance between them. The matching is performed in a series of images depicting the same scene, but in different resolutions, i.e., in a resolution pyramid. Using this hierarchical structure reduces the computational load sig-nificantly. The algorithm is reasonably simple to implement, and it will be shown that it is quite insensitive to noise and other disturbances.

Distance transform are applied to binary feature images, such as those resulting from edge detection. Each pixel is labeled with a number to represent its distance from the nearest feature pixel. The real Euclidean distance to pixels is too expensive to calculate and for most applications an estimate can be used. These include 1-2, 3-4 transforms and other more complicated approximations. In the predistance image, each non-edge pixel is given a value that is a measure of the distance to the nearest edge pixel. The edge pixels get the value zero. The true Euclidean distance is resource demanding (time, mem-ory) to compute, therefore an approximation is used. The operation converting a binary image to an approximate distance image is called a distance transformation (DT). It is important that the DT used in the matching algorithm is a reasonably good approximation of the Euclidean dis-tance; otherwise the discriminating ability of the match-ing measure, computed from the distance values, be-comes poor (G.Borgefors, [5]).

The DT used in the HCMA. This DT uses iterated local opera-tions. The basic idea is that propagating local distances, i.e., distances between neighboring pixels, over the image, approximate global distances in the image. The propagation of local distances can be done either in par-allel or sequentially. Sequential DT's are known as "chamfer" distances, hence "chamfer matching."

2.3 Bootstrap Re - sampling Strategy

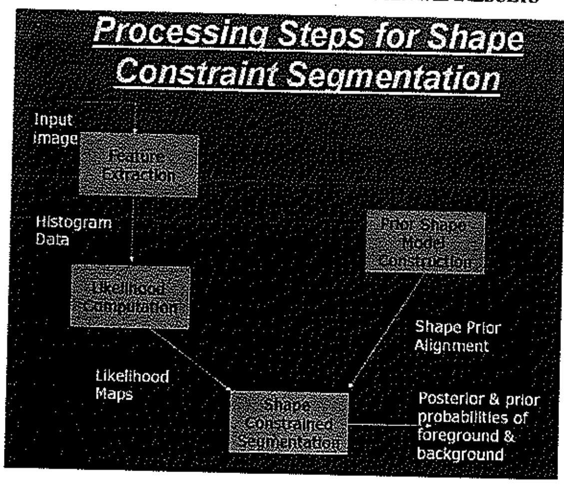
The problem of over fitting is of major importance for all machine learning tasks, regardless of whether they are supervised, i.e., ground-truth label information is available, or unsupervised, i.e., one has to rely solely on the measured features. The learning procedure is supposed to infer the structural characteristics of a data set while avoiding representing statistical fluctuations and, thus, the measurement noise [1].

According to B. Efron and R.J. Tibshirani [10], alleviate the data problem; resampling techniques can be used to generate multiple instances of the available data. One of the most prominent techniques is the bootstrap method [10]. We will utilize the bootstrap framework in order to assess the stability of segmentation solutions generated by the sPDC approach with respect to variations in the input image data. Here, the direct application of resampling by drawing with replacement cannot be applied. This is due to the fact that some of the pixels will be drawn more than once, while others are not chosen at all. Therefore, the basic bootstrap sampling scheme will lead to images in which a certain fraction of pixels that are not selected (i.e., blank or black pixels). In order to fill the holes in the "synthesized" image, we propose randomly drawing a replacement from the_Δ*Δ vicinity of that pixel in the original image data}

Algorithm For Bootstrap Resampling

Require: input image I^{input} of size s=n*m;
Vicinity size Δ
Ensure: bootstrap $I^{bootstrap}$
generate set B_l of (location, value) -
pairs by drawing s times
with replacement
from I^{input}
populate $I^{bootstrap}$ with (location, value)
pairs from B_l
for each location l of $I^{bootstrap}$ €! B_l do
randomly draw value v from local Δ-
vicinity of l in I^{input}
end for.

3. Implementation Steps And Experimental Results



Processing Pipeline for Shape Constrained Segmentation

When we presented with standard image, it is first processed by feature extraction algorithm of PDC framework that is histograms of image sites are acquired. The features, which are subject to histograms in procedure, are the values of three-color channels of the original image together with the magnitudes of the Gabor filter bank.

Shape based image segmentation starts with feature extraction representations of images. These features are usually corners and edges. Standard edge and corner detection algorithms such as sobel filtering and canny edge detection can be applied to color or grey images to generate binary feature maps [15].

Shape constrained image segmentation is implemented by using MATLAB image processing tools and statistical tools. For Parametric distributional Clustering we use EM.m for one dimension we use a general purpose image database containing images from COREL and Berkeley Dataset. All images have size of 256x256 pixels.

During the implementation, we use a platform of Pentium 3.06 GHZ CPU with 1G RAM. Image database consists of wild animals went through image segmentation algorithm. The goal of this work is to provide an empirical basis for research on image segmentation and boundary detection. I have used this data for developing Shape constrained image segmentation [1].

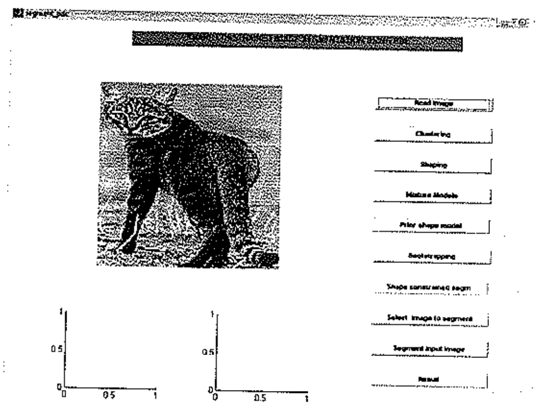


Figure 3.1: Input Image

3.1 Parametric Distributional Clustering

The dataset is considered to be generated by a mixture of Gaussian mixture models, where the cluster probabilities p (.) denotes the mixing coefficients of the model. By virtue of the generative model, we can derive clustering objective via a maximum likelihood approach. The Expectation Maximization Algorithm addresses the problem of determining the values of the free parameters for a given dataset. The Mappings of image sites to clusters is done in E Step, whereas the parameters for the continuous mixture models are fitted in the M-Step.

The input data for the PDC based approach to image segmentation are histograms of feature values taken at image sites lying on a regular grid. The features, which were subject to histogramming procedure, are the values of three color channels of the original input image together with the magnitudes of the Gabor filter bank.

The data from feature extraction is fed to an EM.m program to perform PDC. Once all images are extracted, EM will perform Parametric Distributional Clustering. PDC belongs to the category of segmentation techniques.

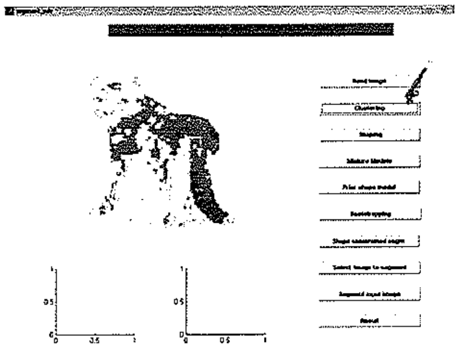


Figure 3.2 : Parametric Distributional Clustering

3.2 Shaping Model

To integrate shape knowledge in to the segmentation process, the problem of adequate representation has to be addressed. Although the method of shape-constrained segmentation, which is presented here, demonstrates very generic characteristics, its application context covers the identification of a wild cat in image of its natural environment. For real world applications, it is evident that images not only contain instances of objects of interest, but also large amounts of background pixels. This background is usually composed of clutter with few discernable shape properties; it can embody a broad variety of different distributions of elementary features. Therefore, one key issue concerning the successful application of shape constraints in a segmentation procedure is given by the ability to automatically identify those regions in an input image, which are likely to depict an object of the semantic category in which one is interested.

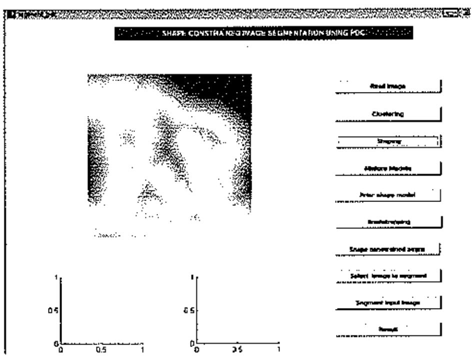


Figure 3.3 : Shaping Model

3.3 Gaussian Mixture Model

The most important class of finite mixture models are *Gaussian mixtures*. The reason for the importance and widespread use of Gaussian mixtures are incidental, but include the fact that a Gaussian has a simple and concise representation requiring only two parameters: the mean μ and the covariance Σ.

To set a proper number of objects per image during PDC, we compute the Gaussian distributions for the parameters mean, and covariance, & MLE (Maximum Likelihood Computation). The PDC segmentation method characterizes image parts by mixtures of Gaussians, which define prototypical distributions for the measured features. Hence, it concisely summarizes the statistical properties of image regions. The key idea used here is to utilize these mixture distributions in order to discern image regions depicting the object of interest from those, which merely display background clutter.

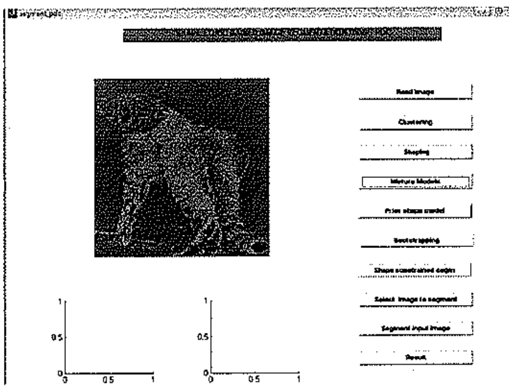


Figure 3.4 : Gaussian Mixture Model

3.4 Prior Shape Model

As a first step in the construction of a prior shape model for standing wild cat in sideward view, image is processed by a distance transform (chamfering). In the next step Gaussian probability function is applied to the distances, transforming them into probabilities while leading to a steep decay of values in the outer regions of image. Having averaged the shape probabilities, an additional Gaussian blurring with a stencil size of 10x10 pixels is applied.

Another method, which we have implemented, for prior shape model construction is, we will start with a single object of interest in which we capture its essential shape properties, applying the distance transform and the Gaussian model to this single image. In such a way the shape constrained segmentation approach can be utilized in content-based image retrieval system with user interaction.

Distance transforms are an important tool in computer vision, images processing and pattern recognition. A distance transform of a binary image specifies the distance from each pixel to the nearest non-zero pixel. Distance transforms play a central role in the comparison of binary images, particularly for images resulting from local feature detection techniques such as edge, arc, corner detection both the chamfers [23] matching approaches make use of distance transforms in comparing binary images. Distance transforms are also used to compute the medial axes of digital shapes [23].

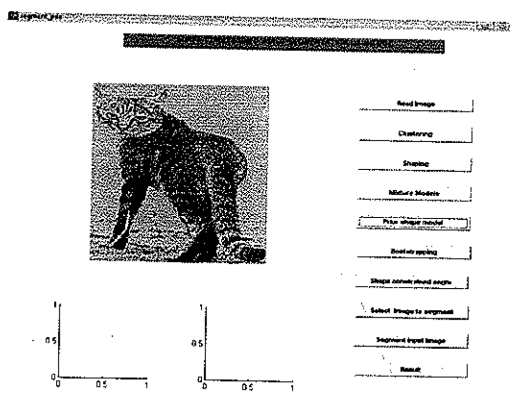


Figure 3.5 : Prior Shape Model

3.5 Bootstrap Resampling

The problem of over fitting is of major importance for all machine learning tasks, regardless of whether they are supervised, i.e., ground-truth label information is available, or unsupervised, i.e., one has to rely solely on the measured features. The learning procedure is supposed to infer the structural characteristics of a data set while avoiding representing statistical fluctuations and, thus, the measurement noise. The data at hand are assumed to originate from a stochastic source which is characterized by a statistical distribution law. Consequently, the measured feature information is considered to result from a sampling process.

To alleviate the data problem, re sampling techniques can be used to generate multiple instances of the available data. One of the most prominent techniques is the bootstrap method [1]. We will utilize the bootstrap framework in order to assess the stability of segmentation solutions generated by the sPDC approach with respect to variations in the input image data. Here, the direct application of re sampling by drawing with replacement cannot be applied. This is due to the fact that some of the pixels will be drawn more than once, while others are not chosen at all. Therefore, the basic bootstrap sampling scheme will lead to images in which a certain fraction of pixels that are not selected (i.e., blank or black pixels). In order to fill the holes in the "synthesized" image, we propose randomly drawing a replacement from the_ $\Delta*\Delta$ vicinity of that pixel in the original image data} . Any dataset not only contains structural information about the nature of the source, but also random fluctuations. Optimally adapting the learning algorithm to the training data thus most often results in also modeling the noise.

Stable edges are emphasized by averaging boundaries over the set of bootstrap samples, while edge pieces that resulted from optimization artifacts or intensity fluctuations are diminished. The gain can be attributed to resampling strategy are diminished.

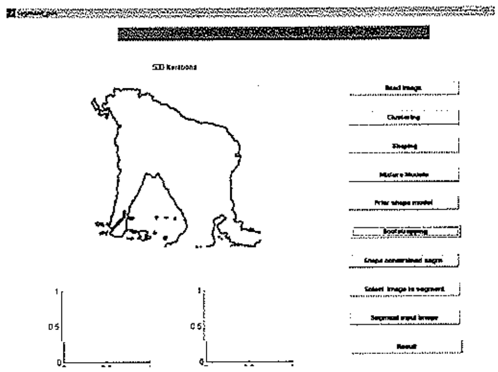


Figure 3.6 : Bootstrap Resampling

3.6 Shape Constrained Image Segmentation

Probably assessment for the semantic categories into segmentation for the input image, each image site is assigned a label according to the maximum of posterior probability values for the foreground and background respectively. After computing label, one sweep of post processing step has been applied to the segmentation in which each site is relabeled. Another post processing step is applied in which all regions with area bellow the aforementioned threshold are eliminated.

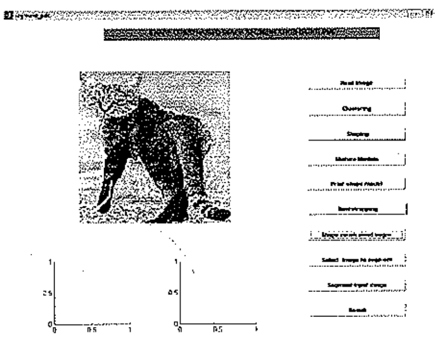


Figure 3.7 : Shape Constrained Image Segmentation

4. Future Enhancements And Conclusion

- Image segmentation as a learning problem requires inferring robust partitioning of image patches with generalization to novel images of the same type
- The bottom up approach favors smooth groupings of image patches and increases the robustness of image segmentation decisions by resampling.
- The top down information flux carries knowledge of object shapes to facilitate segmentation
- The second enhancement of PDC introduces a priori shape information as a guiding principle for segmentation
- A set of various aspects capture a properties of the foreground objects as well as background clutter
- The resulting posteriori probability for occurrence of an object of a specified semantic category has been demonstrated to achieve satisfactory segmentation quality on test bed images from Corel gallery.

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