A Novel Technique for Robust Image Segmentation

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***Abstract*– Image segmentation is an important processing step in many image, video and computer vision applications. Automated segmentation of images has been considered an important intermediate processing task to extract semantic meaning from pixels. The sensitivity of segmentation solutions to image variations is measured by image re-sampling. For any learning algorithm, the problems of robustness towards 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. Shape information is included in the inference process to guide ambiguous groupings of colour and texture features. Shape and similarity-based grouping information is combined into a semantic likelihood map in the framework of Bayesian statistics.**

***Index Terms*– Clustering, Image Segmentation, Mixture Models, Re-sampling and Shape Analysis**

I. INTRODUCTION

IN computer vision, image segmentation refers to the process of partitioning a digital image into multiple segments (sets of pixels, also known as super-pixels). 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. Image segmentation as a learning problem requires inferring a robust partitioning of image patches with generalization to novel images of the same type. The automated segmentation of images into semantically meaningful parts requires shape information since low level feature analysis alone often fails to reach this goal. In this paper, the segmentation process is implemented by a Parametric Distributional Clustering framework (PDC). PDC is combined with coarse shape information. Data groups are represented by continuous mixture models for colour and texture feature distribution. 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 re-sampling. In PDC continuous mixture models for colour and texture feature distributions represent framework data groups whereas 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.

II. LITERATURE SURVEY

Mario A. T. Figueiredo et al. (2004) propose a new approach to model-based clustering under prior knowledge. The proposed formulation can be interpreted from two different angles: as penalized logistic regression, where the class labels are only indirectly observed (via the probability density of each class); as finite mixture learning under a grouping prior. To estimate the parameters of the proposed model, EM algorithm with a closed-form E-step, in contrast with other recent approaches to semi-supervised probabilistic clustering which require Gibbs sampling or suboptimal shortcuts is proposed. They have introduced an approach to probabilistic semi-supervised clustering which is particularly suited for image segmentation.

Nikolaos Nasios et al. (2005) present a variational Bayesian framework for image segmentation using colour clustering. A Gaussian mixture model is used to represent colour distributions. Variational expectation- maximization (VEM) algorithm takes into account the uncertainty in the parameter estimation ensuring a lower bound on the approximation error. In the variational Bayesian approach the distribution of parameters is integrated. The processing task in this case consists of estimating the hyper-parameters of these distributions.

Zhuowen Tu et al. (2005) present a Bayesian framework for parsing images into their constituent visual patterns. The parsing algorithm optimizes the posterior probability and outputs a scene representation in a "parsing graph", in a spirit similar to parsing sentences in speech and natural language. The algorithm constructs the parsing graph and re-configures it dynamically using a set of reversible Markov chain jumps. This computational framework integrates two popular inference approaches – generative (top-down) methods and discriminative (bottom-up) methods.

Mahinda P. Pathegama et al. (2005) show that extraction of edge-end-pixels is an important step for the edge linking process to achieve edge-based image segmentation. This paper presents an algorithm to extract edge-end pixels together with their directional sensitivities as an augmentation to the currently available mathematical models. The algorithm is implemented in the Java environment because of its inherent compatibility with web interfaces since its main use is envisaged to be for remote image analysis on a virtual instrumentation platform.

A. Nakib et al. (2007) propose a microscopic image segmentation method with two-dimensional (2D) exponential entropy based on hybrid micro-canonical annealing. The 2D maximum exponential entropy does not consider only the distribution of the gray-level information but also takes advantage of the spatial information using the 2D-histogram. In this paper, they proposed a new approach to find optimal thresholds, based on hybrid micro-canonical optimization. In the first phase the two dimensional histogram was constructed using spatial information, local average gray value, to choose optimal thresholds. In the second phase, a new extension of the one-dimensional exponential entropy to the two-dimensional case and its generalization to multilevel segmentation were developed. In the third phase, micro-canonical annealing (MA) is introduced to remove the stochastic feature of the solution. This approach allows for good microscopic image segmentation by using exponential two-dimensional entropy.

III. DESIGN AND IMPLEMENTATION

A. Parametric Distributional Clustering

Clustering is one of the possible approaches to effective organization and retrieval of images. In a simplistic statement, clustering is the division of a set of observations into groups based on some predefined criterion and a similarity measure. In order to characterize a clustering procedure the modular has to specify the objects, which are to be, clustered, the nature of the feature associated with these objects and the criteria on which the grouping is based. The basic objects on which clustering method operated are image sites s. s = {s} with | s | = n. This set s is partitioned into k groups. The cluster memberships are encoded by m where m(s) = c denotes the side s is mapped to cluster c. Every site s is equipped with a set of observations. PDC segmentation method characterizes image part by mixture of a Gaussians, which defines prototypical distributions or the measured features. Generative model for individual observation is given

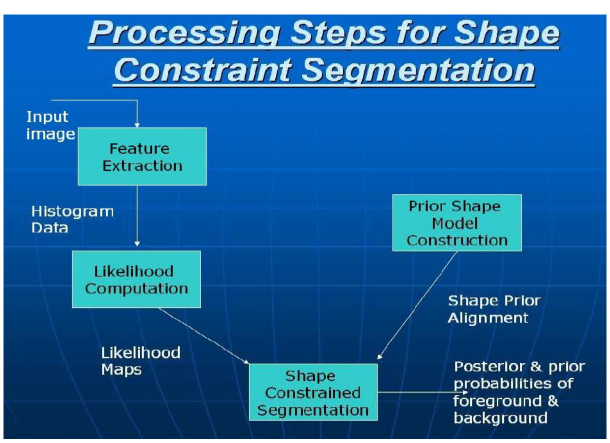

Fig. 1: Processing Pipeline for Shape Constrained Segmentation

by the group membership m(s) of its associated site s is defined as:

$$p(x|m(s)) = \sum_{\alpha=1}^{l} p_{\alpha|m(s)} g_{\alpha}(x) \quad (1)$$

$g\alpha(x) = g(x|\mu\alpha, \Sigma\alpha)$ denotes multivariate Gaussian distribution with mean $\mu\alpha$ and covariance $\Sigma\alpha$

B. Prior Shape Model Construction

To integrate shape knowledge into the segmentation process, the problem of adequate representation has to be addressed. Rigid objects which are always presented in the same pose certainly demand a less variegated description than flexible objects which are depicted in a rich variety of different possible poses. One key issue concerning the successful application of shape constraints in 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.

C. Semantic Likelihood Maps

For real world applications it is evident, that given images not only contain instances of the sought-after objects, but also large amounts of background pixels. Although this background usually is composed of clutter with little discernable shape properties, it can embody a broad variety of different distributions of elementary image features. 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. Once we have PDC segmentations for a given database of images at hand, representative feature distributions for the semantic category of interest as well as the background can be selected by user interaction. The goal the approach to shape driven image partitioning is to utilize shape constraints in order to satisfactorily segment images, which contain objects of a certain semantic category.

D. Bootstrap Re-sampling

Re-sampling techniques can be used to generate multiple instances of the available 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 results in modelling the noise. Consequently the performance of unseen examples deteriorates which is known as over fitting. The problem of over fitting is of major importance for all machine learning task regardless whether they are unsupervised are supervised. The learning procedure is supposed to infer structural characteristic of a dataset while avoiding representative statistical fluctuation and thus the measurement noise. The major feature information is considered to result from a sampling process. The bootstrap framework is utilized in order to assess the stability of segmentation solutions generated by the sPDC approach with respect to variations in the input image data.

E. Combining Shape and Segmentation

A statistical representation of shape and derived likelihood maps for the semantic categories *foreground object* and *background* is established. Now, these two sources of information about object identity have to be fused to arrive at a segmentation of a given input image into areas corresponding to these categories. As both types of information are provided in a probabilistic form, it is most natural to combine them in the framework of Bayesian statistics. To this end, the shape information concerning the foreground object is interpreted as the prior and will henceforth be denoted by P_S. Formally, the posterior probability $P_{\omega f}$ of the foreground semantic category at site **s** is computed by:

$$P_{\omega_f}(s) = \frac{p^{\omega_f}(\mathrm{s}) \cdot P_S(\mathrm{s})}{p^{\omega_f}(\mathrm{s}) \cdot P_S(\mathrm{s}) + p^{\omega_b}(\mathrm{s}) \cdot (1 - P_S(\mathrm{s}))} \quad (2)$$

IV. EXPERIMENTAL RESULTS

Shape constrained image segmentation using re-sampling is implemented by using MATLAB image processing tools and statistical tools.

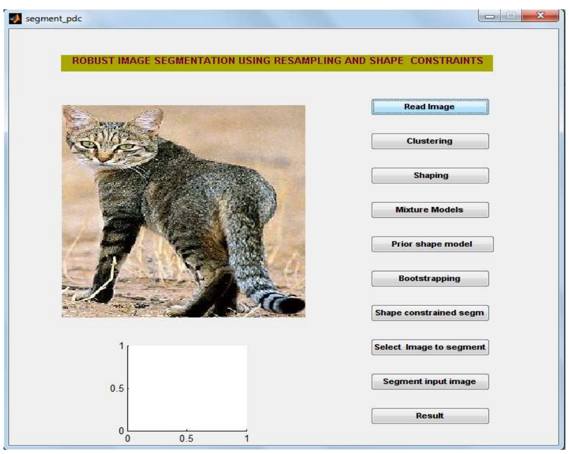

Fig. 2: Input Image

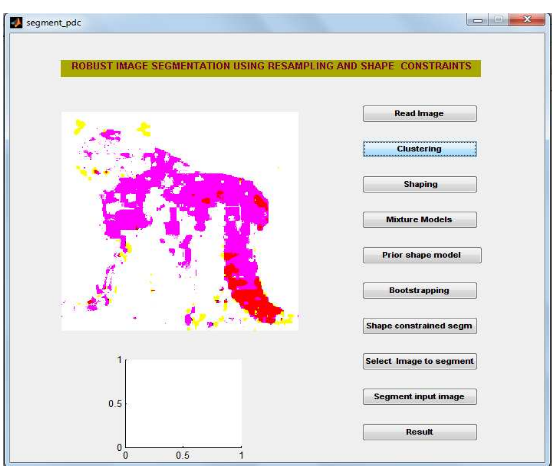

Fig. 3: Parametric Distributional Clustering

A. 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. 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 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.

B. Shaping Model

To integrate shape knowledge into the segmentation process, the problem of adequate representation has to be addressed. Although the method of shape-constrained segmentation, demonstrates very generic characteristics, its application context covers the identification of a wild cat in image of its natural environment. The 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.

C. 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 μand 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.

D. 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. In such a way the shape constrained segmentation approach can be utilized in content-based image retrieval system with user interaction.

E. Bootstrapping

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. 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. The bootstrap framework is utilized in order to assess the stability of segmentation solutions generated by the sPDC approach with respect to variations in the input image data.

F. 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 relabelled. Another post processing step is applied in which all regions with area below the aforementioned threshold are eliminated.

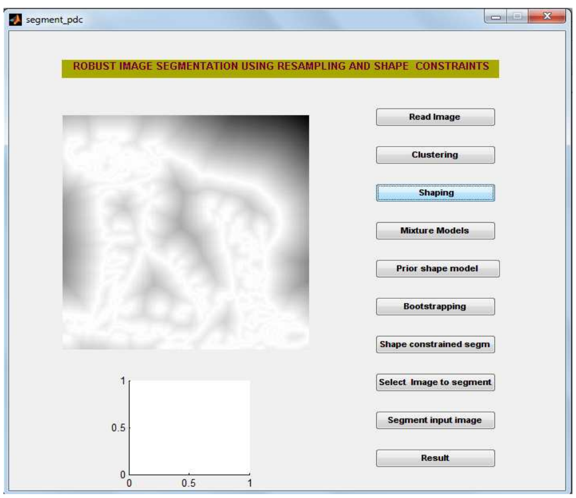

Fig. 4: Shaping Model

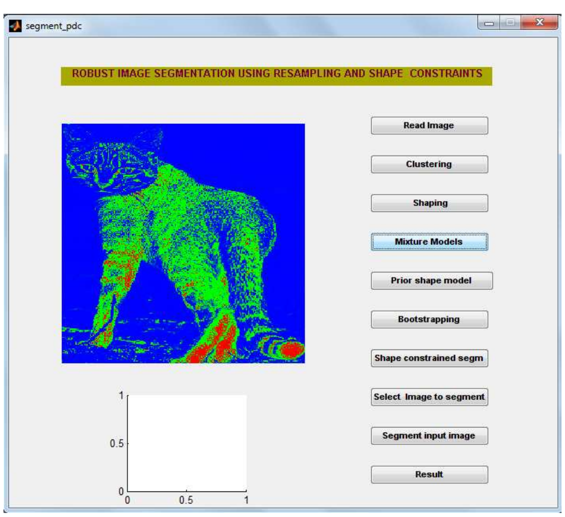

Fig. 5: Gaussian Mixture Model

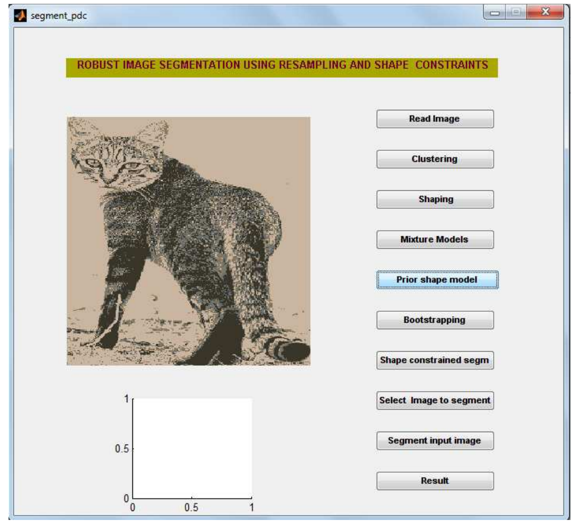

Fig. 6: Prior Shape Model

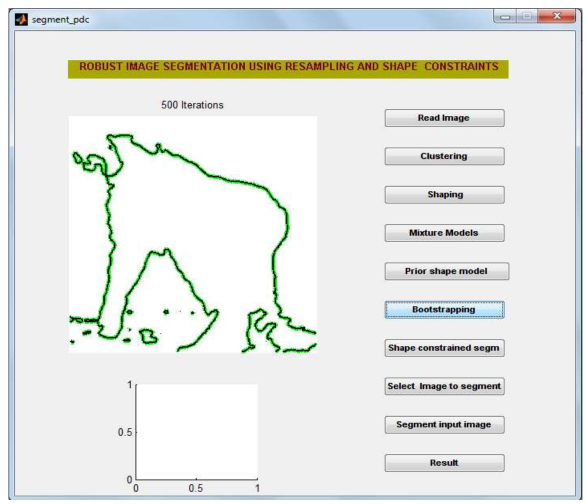

Fig. 7: Bootstrapping

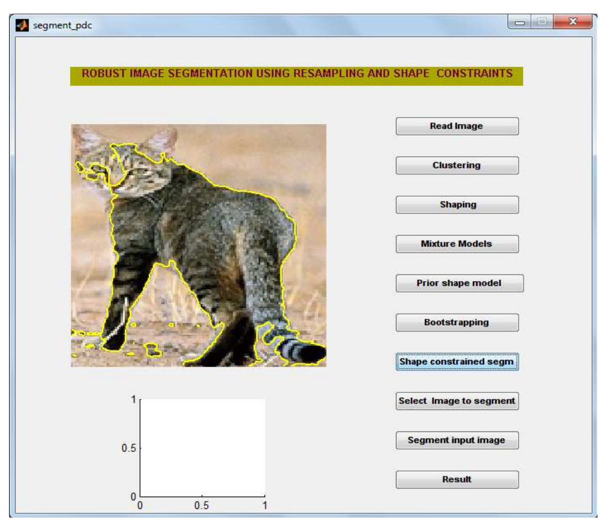

Fig. 8: Shape-constrained Image Segmentation

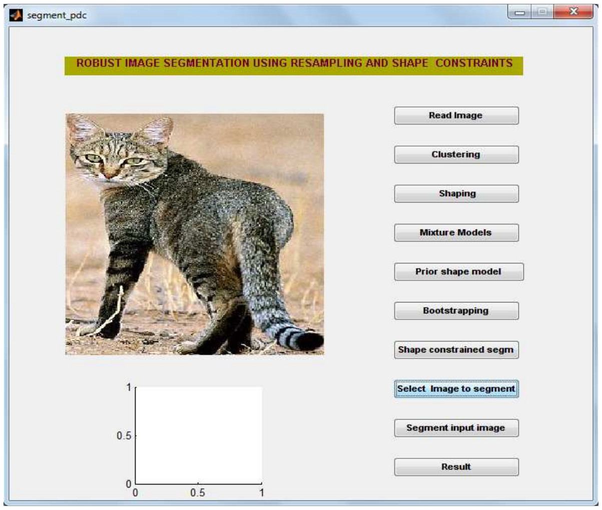

Fig. 9: Select Image to Segment

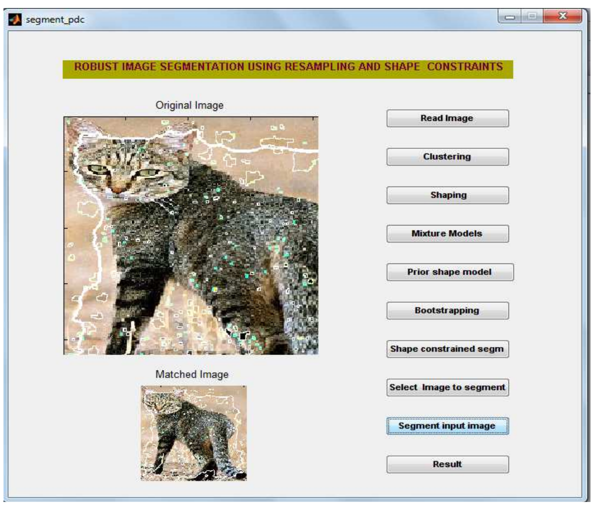

Fig. 10: Segment Input Image

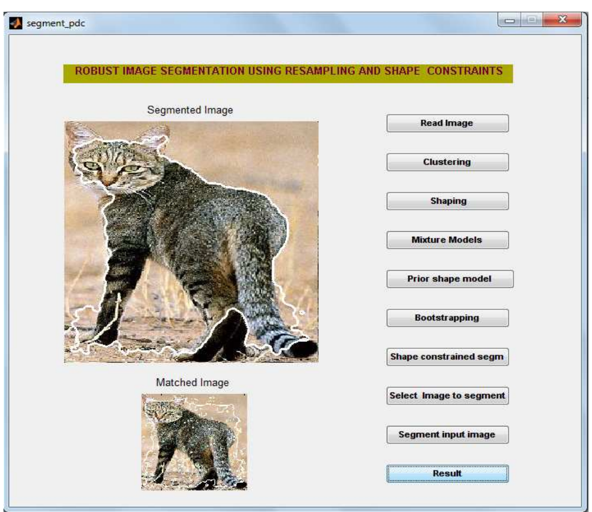

Fig. 11: Results

V. CONCLUSION AND FUTURE ENHANCEMENTS

In this contribution, a novel model for unsupervised image segmentation has been proposed. It is based on robust measurements of local image characteristics given by feature histograms. As one of the main contributions, it contains a continuous model for the group-specific distributions:

- 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 favours smooth groupings of image patches and increases the robustness of image segmentation decisions by re-sampling
- 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 posterior 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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