UNIVERSITÀ DEGLI STUDI DI PADOVA

Mean shift clustering

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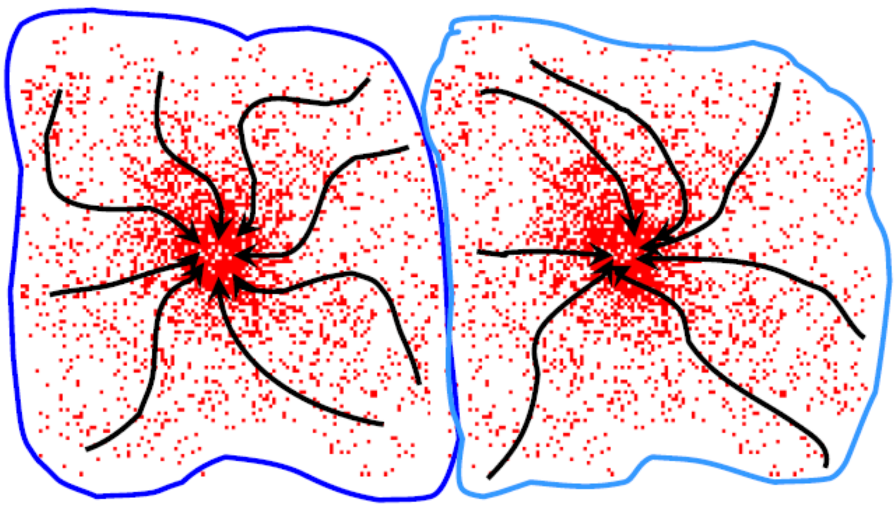
Agenda

- Clustering criterion
- Clustering in multiple dimensions
- Examples

Mean shift clustering

- Clustering criterion
  - Define attraction basin as the region for which all trajectories lead to the same mode
  - All data points in the attraction basin are merged into a cluster



Mean shift key paper

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IAS-LAB

Key paper:

D. Comaniciu, P. Meer, "Mean shift: A robust approach toward feature space analysis", *IEEE Transactions on pattern analysis and machine intelligence*, *24*(5), 603-619, 2002.

- Available on moodle

IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, VOL. 24, NO. 5, MAY 2002 603

Mean Shift: A Robust Approach Toward Feature Space Analysis

Dorin Comaniciu, *Member*, *IEEE*, and Peter Meer, *Senior Member*, *IEEE*

Abstract—A general nonparametric technique is proposed for the analysis of a complex multimodal feature space and to delineate arbitrarily shaped clusters in it. The basic computational module of the technique is an old pattern recognition procedure, the mean shift. We prove for discrete data the convergence of a recursive mean shift procedure to the nearest stationary point of the underlying density function and, thus, its utility in detecting the modes of the density. The relation of the mean shift procedure to the Nadaraya-Watson estimator from kernel regression and the robust M-estimators of location is also established. Algorithms for two low-level vision tasks, discontinuity preserving smoothing and image segmentation, are described as applications. In these algorithms, the only user set parameter is the resolution of the analysis and either gray level or color images are accepted as input. Extensive experimental results illustrate their excellent performance.

Index Terms—Mean shift, clustering, image segmentation, image smoothing, feature space, low-level vision.

1 INTRODUCTION

LOW-LEVEL computer vision tasks are misleadingly difficult. Incorrect results can be easily obtained since the employed techniques often rely upon the user correctly guessing the values for the tuning parameters. To improve performance, the execution of low-level tasks should be task driven, i.e., supported by independent high-level information. This approach, however, requires that, first, the low-level stage provides a reliable enough representation of the input and that the feature extraction process be controlled only by very few tuning parameters corresponding to intuitive measures in the input domain.

Feature space-based analysis of images is a paradigm which can achieve the above-stated goals. A feature space is a mapping of the input obtained through the processing of the data in small subsets at a time. For each subset, a parametric representation of the feature of interest is obtained and the result is mapped into a point in the multidimensional space of the parameter. After the entire input is processed, significant features correspond to denser regions in the feature space, i.e., to clusters, and the goal of the analysis is the delineation of these clusters.

The nature of the feature space is application dependent. The subsets employed in the mapping can range from individual pixels, as in the color space representation of an image, to a set of quasi-randomly chosen data points, as in the probabilistic Hough transform. Both the advantage and the disadvantage of the feature space paradigm arise from the global nature of the derived representation of the input. On one hand, all the evidence for the presence of a significant feature is pooled together, providing excellent tolerance to a noise level which may render local decisions unreliable. On the other hand, features with lesser support in the feature space may not be detected in spite of being salient for the task to be executed. This disadvantage, however, can be largely avoided by either augmenting the feature space with additional (spatial) parameters from the input domain or by robust postprocessing of the input domain guided by the results of the feature space analysis.

Analysis of the feature space is application independent. While there are a plethora of published clustering techniques, most of them are not adequate to analyze feature spaces derived from real data. Methods which rely upon a priori knowledge of the number of clusters present (including those which use optimization of a global criterion to find this number), as well as methods which implicitly assume the same shape (most often elliptical) for all the clusters in the space, are not able to handle the complexity of a real feature space. For a recent survey of such methods, see [29, Section 8].

In Fig. 1, a typical example is shown. The color image in Fig. 1a is mapped into the three-dimensional L*u*v* color space (to be discussed in Section 4). There is a continuous transition between the clusters arising from the dominant colors and a decomposition of the space into elliptical tiles will introduce severe artifacts. Enforcing a Gaussian mixture model over such data is doomed to fail, e.g., [49], and even the use of a robust approach with contaminated Gaussian densities [67] cannot be satisfactory for such complex cases. Note also that the mixture models require the number of clusters as a parameter, which raises its own challenges. For example, the method described in [45] proposes several different ways to determine this number.

Arbitrarily structured feature spaces can be analyzed only by nonparametric methods since these methods do not have embedded assumptions. Numerous nonparametric clustering methods were described in the literature and they can be classified into two large classes: hierarchical clustering and density estimation. Hierarchical clustering techniques either aggregate or divide the data based on

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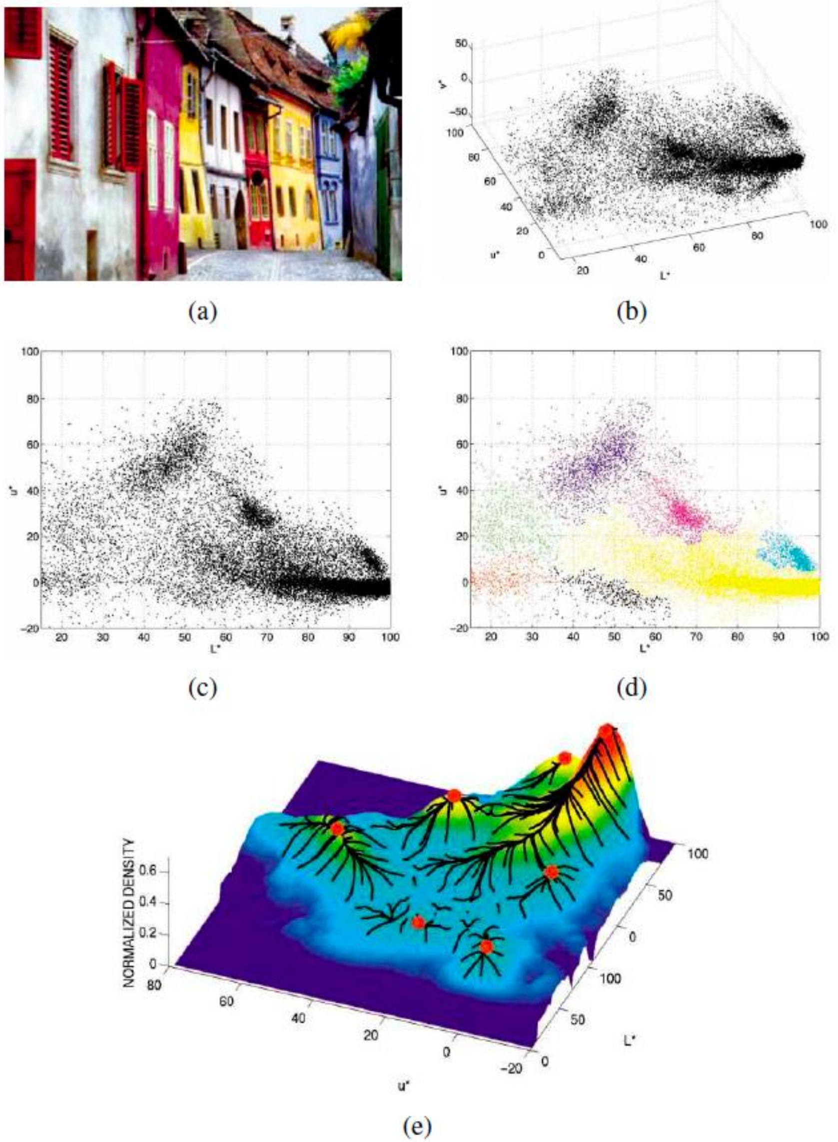
For information on obtaining reprints of this article, please send e-mail to: tpami@computer.org, and reference IEEECS Log Number 113483.

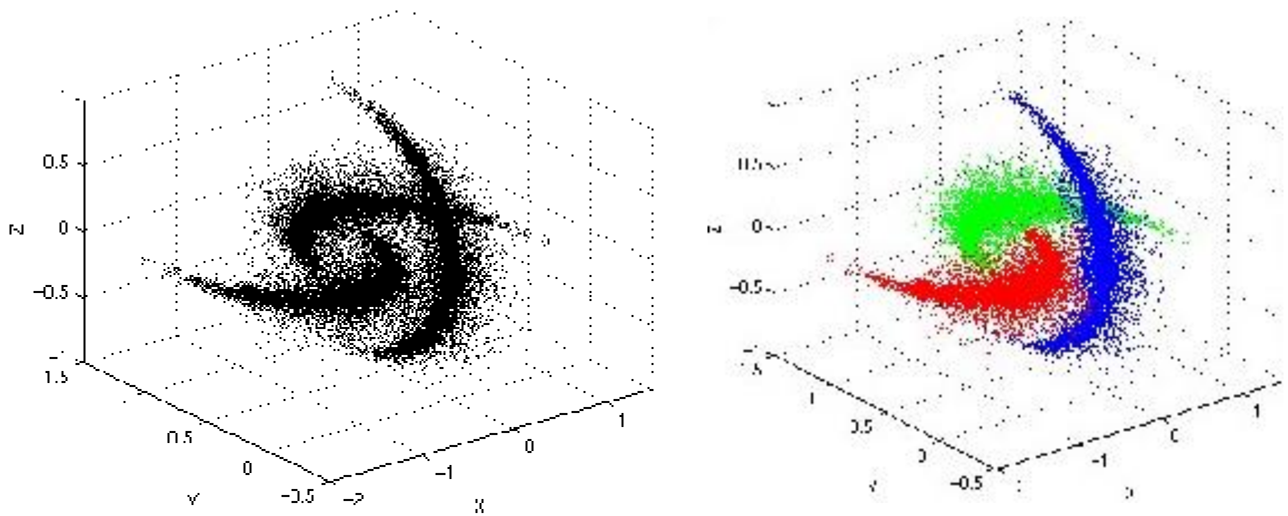
Mean shift clustering

- Example of mapping
  - Input image
  - Pixel plotted in L*u*v space
  - L*u space distribution
  - Clusters after 159 mean-shift procedures
  - Corresponding trajectories with peaks marked as red dots



Mean shift clustering

- Mean-shift can effectively separate complex modal structures



Preserving discontinuities

- It is possible to preserve discontinuities
  - Joint domain: spatial + color

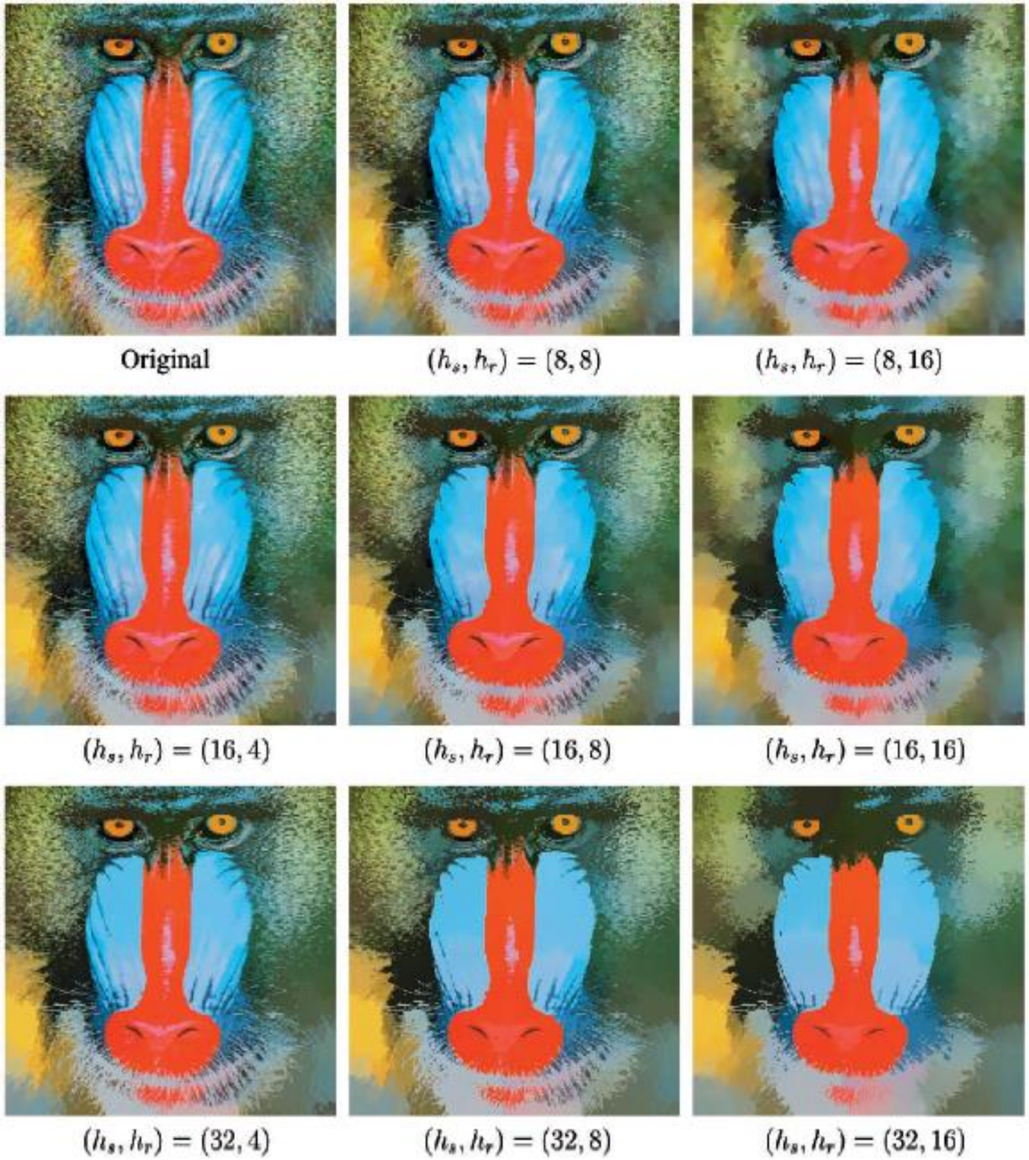
$$K(x) = c_k \cdot k_s\left(\frac{\boldsymbol{x}_s}{r_s}\right) \cdot k_s\left(\frac{\boldsymbol{x}_r}{r_r}\right)$$

Where:

- $\boldsymbol{x}_s$ are the spatial coordinates
- $\boldsymbol{x}_r$ are the color coordinates

Spatial vs color window

- Effect of window size
  - Spatial range (vertical)
  - Color range (horizontal)



Preserving discontinuities

- Preserving discontinuities

Preserving discontinuities

- Preserving discontinuities

MS segmentation – example

Original

Features: position + gray

Features: gray level only

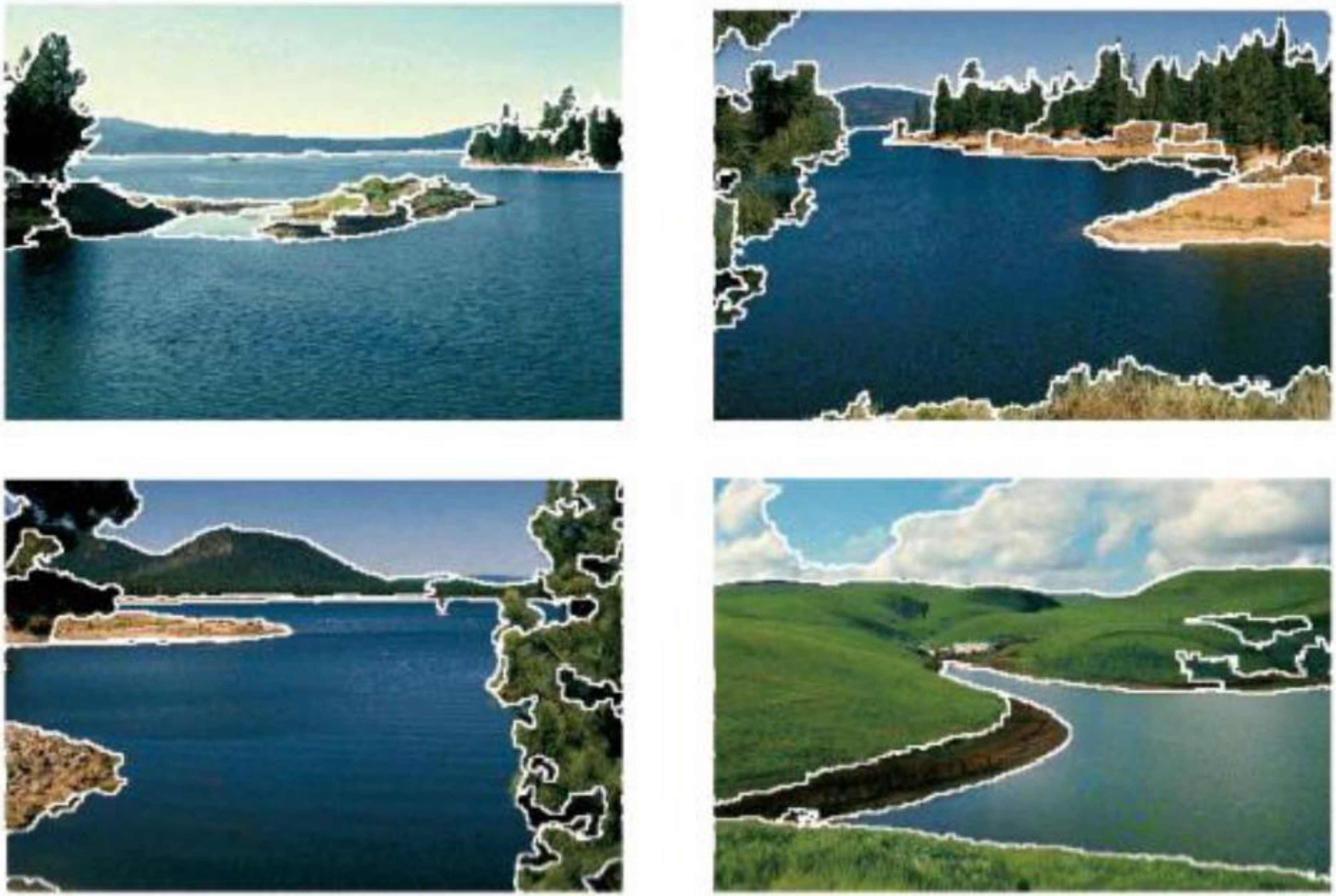
MS segmentation – examples

MS segmentation – examples




MS segmentation – examples

MS segmentation – examples



MS segmentation – examples

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