Abstract

With the optimization of pattern discrimination as a goal, graph partitioning approaches often lack the capability to integrate prior knowledge to guide grouping. In this paper, we consider priors from unitary generative models, partially labeled data and spatial attention. These priors are modelled as constraints in the solution space. By imposing uniformity condition on the constraints, we restrict the feasible space to one of smooth solutions. A subspace projection method is developed to solve this constrained eigenproblem. We demonstrate that simple priors can greatly improve image segmentation results.

1 Introduction

Grouping is often thought of as the process of finding intrinsic clusters or group structures within a data set. In image segmentation, it means finding objects or object segments by clustering pixels and segregating them from background. It is often considered a bottom-up process. Although never explicitly stated, higher level of knowledge, such as familiar object shapes, is to be used only in a separate post-processing step.

The need for the integration of prior knowledge arises in a number of applications. In computer vision, we would like image segmentation to correspond directly to object segmentation. In data clustering, if users provide a few examples of clusters, we would like a system to adapt the grouping process to achieve the desired properties. In this case, there is an intimate connection to learning classification with partially labeled data.

We show in this paper that it is possible to integrate both bottom-up and top-down information in a single grouping process. In the proposed method, the bottom-up grouping process is modelled as a graph partitioning [1, 4, 12, 11, 14, 15] problem, and the top-down knowledge is encoded as constraints on the solution space. Though we consider normalized cuts criteria in particular, similar derivation can be developed for other graph partitioning criteria as well. We show that it leads to a constrained eigenvalue problem, where the global optimal solution can be obtained by eigendecomposition. Our model is expanded in detail in Section 2. Results and conclusions are given in Section 3.