Abstract

We define a predicate for measuring the evidence for a boundary between two regions using a graph-based representation of the image. We then develop an efficient segmentation algorithm based on this predicate, and show that although this algorithm makes greedy decisions it produces segmentations that satisfy global properties. We apply the algorithm to image segmentation using two different kinds of local neighborhoods in constructing the graph, and illustrate the results with both real and synthetic images. The algorithm runs in time nearly linear in the number of graph edges and is also fast in practice. An important characteristic of the method is its ability to preserve detail in low-variability image regions while ignoring detail in high-variability regions.

Introduction

A wide range of computational vision problems could in principle make good use of segmented images, were such segmentations reliably and efficiently computable. For instance intermediate-level vision problems such as stereo and motion estimation require an appropriate region of support for correspondence operations. Spatially non-uniform regions of support can be identified using segmentation techniques. Our goal is to develop computational approaches to image segmentation that are broadly useful, much in the way that other low-level techniques such as edge detection are used in a wide range of computer vision tasks. In order to achieve such broad utility. While the past few years have seen considerable progress in eigenvector-based methods of image segmentation (e.g., Shi and Malik, 1997; Weiss, 1999), these methods are too slow to be practical for many applications. In contrast, the method described in this paper has been used in large-scale image database applications as described in Ratan et al. (1999). While there are other approaches to image segmentation that are highly efficient, these methods generally fail to capture perceptually important non-local properties of an image as discussed below.

Review of Literature

Our method is based on selecting edges from a graph, where each pixel corresponds to a node in the graph, and certain neighboring pixels are connected by undirected edges. Weights on each edge measure the dissimilarity between pixels. However, unlike the classical methods, our technique adaptively now turn to a simple synthetic example illustrating some of the non-local image characteristics captured by our segmentation method. Consider the image shown in the top left .Most people will say that this image has three distinct regions: a rectangular shaped intensity ramp in the left half, a constant intensity region with a hole on the right half, and a high-variability rectangular region inside the constant region. This example illustrates some perceptually important properties that we believe should be captured by a segmentation algorithm. Adjusts the segmentation criterion based on the degree of variability in neighboring regions of the image. This results in a method that, while making greedy decisions, can be shown to obey certain obvious global properties. We also show that other adaptive criteria, closely related to the one developed here, result in problems that are computationally difficult (NP hard). One common approach to image segmentation is based on mapping each pixel to a point in some feature space, and then finding clusters of similar points (e.g., Comaniciu and Meer, 1997, 1999; Jain and Dubes, 1988). In this section we investigate using the graphbased segmentation algorithm from Section 4 in order to find such clusters of similar points. In this case, the graph $G = (V, E)$ has a vertex corresponding to each feature point (each pixel) and there is an edge (v_i, v_j) connecting pairs of feature points v_i and v_j that are nearby in the feature space, rather than using neighboring pixels in the image grid. There are several possible ways of determining which feature points to connect by edges.

Model Explanation

In recent times there have been many challenges to reduce the speckle noise using wavelet transform as a multi-resolution image processing tool.

- **Speckle Noise in Ultrasound image**

  Ultrasound image is one of the most widely used diagnostic tools in modern medicine. It is relatively expensive and portable compared to techniques like MRI and CT. It is used to visualize muscles and internal organs and also their structures. It does not use ionizing radiation. So, it does not convey any risk to people.

  Speckle noise affects all kinds of coherent system. In medical literature, speckle noise is referred as “texture” and may contain useful information. In automatic segmentation, maintaining the sharpness of the boundaries in different images region is significant while removing the speckle. For visualizing the image, smoothing the texture may be less desirable. It is essential to develop noise filters that preserve the features that are important.

- **Model of speckle noise**

  A possible generalized model for speckle noise is

$$g(n,m) = f(n,m)\, u(n,m) + \beta(n,m)$$

  where g,f,u and β stands for observed image. When applied to ultrasound image only multiplicative images are considered. So the equation reduces to

$$g_1(n,m) = f_1(n,m)\, u_1(n,m)$$

  At this stage, the problem of de-speckling is reduced to the problem of rejecting an additive noise.

- **Generation of Speckle noise**

The MATLAB command is

$$J = imnoise(I,`speckle`,v)$$

Where I is the noise and v is the noise variance. This adds multiplicative noise to the image I, using the equation

$$J = I + n*I$$

Where n is uniformly distributed random noise with mean 0 and variance v.

- **Wavelet domain noise filtering**

Recently there have been significant investigation in the medical field using the wavelet transformation as a tool for delineating medical images from noisy data. It attempts to preserve the signal characteristics, regardless of its frequency content. As the discrete wavelet transform (DWT) corresponds to the basis decomposition, it provides nonredundant and uniqe representation of the signal.

Conclusion

In this paper we have introduced a new method for image segmentation based on pairwise region comparison. We have shown that the notions of a segmentation being too coarse or too fine can be defined in terms of a function which measures the evidence for a boundary between pairs of regions. Our segmentation algorithm makes simple greedy decisions, and yet produces segmentations that obey the global properties of being not too coarse and not too fine using a particular region comparison function.