Image Segmentation by Level Set Analysis

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Abstract

This paper describes an automated image segmentation technique that subdivides regions of homogeneous texture. The method utilizes a level set analysis of scaled Gabor filter responses. Scaling is achieved via an area morphological process. Each scaled, filtered image is examined to locate important connected components based on minimal total internal variance and maximal edge localization. The candidate segments are selected using a granulometry of the gradient magnitude evaluated at the level lines of the connected components. The level set analysis avoids the high computational cost associated with conventional level set approaches by sampling only the significant level sets for processing. The target application for this segmentation technique is content based image retrieval.

1. Introduction

Segmentation has traditionally been viewed as part of image understanding. A need in image understanding is to organize the raw pixel data such that processing can be focused on specific regions/objects in the scene rather than on the complete scene. In this paper, we are developing a segmentation technique for the purpose of content based retrieval (CBR). The preferred method of access to modern image databases has been via text (metadata) information. However, this approach is not very reliable given the limited semantic encapsulation ability of text keywords and the limited ability to automatically generate metadata. The drawbacks are eliminated if object based information is used for retrieval purposes.

A shortcoming of conventional segmentation schemes used in CBR is the problem of automated parameter selection and adjustment. In this paper we present an automated image segmentation scheme for general imagery. This approach involves extraction of multiple textured regions in an image via a Gabor filterbank. In order to achieve a tradeoff between segmentation localization and matching complexity we utilize an area morphological scaling technique to yield a partition satisfying a minimum scale criterion. We introduce a simple yet efficacious level set analysis algorithm for fast extraction of candidate segments from the scaled Gabor decompositions. Finally a combinatorial analysis of candidate segments yields a segmentation. Segment specific color, texture and shape features are utilized for demonstrating the CBR framework.

2. Segmentation

Typical segmentation algorithms require *ad hoc* parameter tuning for functionality with a variety of real world images. The segmentation approach presented here models images as a composition of multiple textured regions at an appropriate scale. We utilize the Gabor filterbank approach to extract textured regions. Gabor filters are known to optimize the tradeoff between localization in the spatial and frequency domains [3]. Gabor filters are also known to analogous to the biological vision system [3].

A 2-D Gabor function is a complex sinusoidal grating modulated by a 2-D Gaussian function:

$$h(x, y) = g(x', y')\exp[2\pi j(Ux + Vy)], \quad (1)$$

$$g(x, y) = \left(\frac{1}{2\pi\lambda\sigma^2}\right)\exp\left[-\frac{(x/\lambda^2)^2 + y^2}{2\sigma^2}\right]$$

where $(x', y') = (x\cos\phi + y\sin\phi, -x\sin\phi + y\cos\phi)$ gives the rotated coordinates, and $g(x, y)$ is a 2-D Gaussian function with aspect ratio λ, scale

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parameter σ, and major axis oriented at an angle ϕ from the x-axis. The pair (U, V) reveals the center frequencies of the Gabor filter. An image is decomposed into multiple narrow band responses via a comprehensive Gabor filterbank. The Gabor filter frequencies and orientations can be specified in terms of the Gabor half-peak frequency and orientation bandwidths [3]. The Gabor decomposition is used for the dual purpose of segmentation and texture feature extraction. Figure 1 shows a sample image and its Gabor response at a particular center frequency.

The Gabor decomposition contains regions of homogeneous texture as locally maximized regions. It is our goal to extract these regions and classify them as representative of the textured objects in the image. Segment extraction at this stage would not satisfy a minimum scale criterion; hence, we utilize a scaling method based on area morphology.

2.1 Area Morphology

Area morphology operates on image level sets. Level sets are derived from thresholded representations of the original image. The level set parameters range from 0 to g-1 (where g is maximum number of graylevels in the image). The Area Open-Close (AOC) operation [8] can be used to remove connected components within the image level sets that do not meet the specified minimum area/scale. In this CBR application, the minimum area depends on the image granulometry. For a level set $\mathbf{B}$, we can define the area open operation by

$$(x, y) \in \overset{s}{\mathrm{o}}(\mathbf{B}) \text{ if } |\mathbf{C_B}(x, y)| \geq s, \qquad (2)$$

where $|\mathbf{C_B}(x, y)|$ is the cardinality (area in the discrete sense) of the connected component at location (x, y) within $\mathbf{B}$, and s is the minimum area/scale. Likewise, we have $(x, y) \notin \overset{s}{\mathrm{o}}(\mathbf{B})$ if $|\mathbf{C_B}((x, y))| < s$. The area close operation is the dual operation for connected components of 0's in the level set – the area open of the complement of $\mathbf{B}$. For grayscale imagery, each level set is area open-closed independently, and the scaled grayscale image is computed by a stacking operation.

Traditional implementations of the AOC operation have been time consuming given the sequential nature of connected component labeling within the g level sets. Recent advances in area morphology [1], [7] have introduced fast algorithms. A fast algorithm for area open is adapted here for the AOC. As a preliminary step we utilize the standard morphological open filter to create a marker image $\mathbf{M}$ from the original image $\mathbf{I}$., The partial connected components within level sets of marker image $\mathbf{M}$ are fully reconstructed to yield the final reconstruction $\mathbf{R}$. Although the fast algorithm improves vastly upon the computational cost required, it is not equivalent to the area open operation. It should be regarded instead as an approximate algorithm. This is because the opening by reconstruction is not equivalent to an area opening, since some connected components that exceed the area criterion may not survive the opening.

2.1.1. Marker image creation using the open filter.

A morphological open filter with a structuring element $\mathbf{K}$ (which has area a) is applied to the original image $\mathbf{I}$:

$$\mathbf{M} = \mathbf{I} \circ \mathbf{K}. \qquad (3)$$

In this case, the surviving connected components have minimum area of a. This marker image is used as a precursor to the reconstruction process discussed in Section 2.1.2 below. If the area close, as opposed to the area open, is desired, then the close filter is used to create the marker in (3).

2.1.2. Reconstruction by geodesic dilation. In the marker creation process, three outcomes occur. First, connected components of insufficient area are removed. Second, some connected components of sufficient area are removed. Third, connected components of sufficient area that survive the marker process have distorted boundaries. These partial connected components within level sets in the marker image $\mathbf{M}$ are reconstructed based on intensities in the input image $\mathbf{I}$. This is accomplished by geodesic dilation of the partial connected components. If a connected component in the marker image has a neighboring pixel (in 4-connectivity) of lower intensity than that of the input image, then that pixel is increased to the minimum intensity between the dilated image and the input image according to

$$R_t(x, y) = \min\left\{\left(\mathbf{R}_{t-1} \oplus K^+\right)(x, y), I(x, y)\right\} \quad (4)$$

where $\mathbf{R}_0 = \mathbf{M}$, and K^+ is a 3x3 cross-shaped structuring element. (4) converges when reconstruction is accomplished.

Level lines (the boundaries of connected components) are not distorted in the process of AOC filtering. In contrast, the open-close filter distorts level lines based on the inscription of a structuring element. So, artifacts such as corner rounding are common. The AOC, on the other hand, is connected invariant. The filter either entirely removes or preserves an individual connected component in an image level set. The AOC therefore has attractive properties for scaling images and for segmentation [2], [7], [8]. These features include feature causality, Euclidean invariance, and edge preservation through scale. Thus in the context of our CBR application the AOC operator aids in efficient feature extraction. Figure 2 illustrates AOC scaling of a Gabor filter response.

3. Level set analysis of scaled Gabor decompositions

A level set analysis of the scaled Gabor decompositions is implemented to yield a segmentation. Conventional level set analysis algorithms require an exhaustive sampling of the image level sets in order to yield a segmentation. However, we propose to use only the level sets containing well localized objects based on level lines localization. Level line analysis has been applied effectively in recent applications such as disocclusion [5]. Level lines are boundary pixels in level sets. The level lines are invariant to changes in illumination and thus offer considerable advantages over conventional utilization of edge information [5]. The concept of level lines is illustrated in Figure 3.

For a gray-scale image with intensity values ranging from 0 to 255 there would be a maximum of 256 level sets. Several of these level sets differ very slightly from neighboring level sets. Hence, the level sets can be sampled to reduce number of level sets used in the segmentation process. Given a constant level set step size Δb, the level sets would range from 0 to 255 in steps of Δb. A constant step size may skip some important level sets containing important information in the form of objects with strongly localized boundaries. Here, we want to sample only the important level sets, and we use a variable step size determined in an automatic manner. We propose to use the cumulative gradient magnitude from the level lines to determine the level sets to be sampled for purposes of segment extraction.

Consider a level set $\mathbf{B}_l$ such that

$$\mathbf{B}_l(p) = 1 \text{ if } I(p) \geq l, \quad = 0 \text{ Otherwise} \tag{5}$$

where image location $p \in \mathbf{D}$, for the discrete domain $D \subset \mathbf{Z}^2$ and $l \in \mathbf{Z}$. Within these level sets we define the boundary pixels of connected components as level lines. We define the boundary pixels as on the boundary rather than one pixel outside/inside the boundary. We assume a 4-neighborhood system for connected component labeling. Given a connected component $C_{\mathbf{B}l}(p)$, its boundary pixels satisfy the following conditions:

$$N_h(p_c) = \{C_{\mathbf{B}l}(p_c \pm \nabla p)\}, \quad |N_h(p_c) > 0| \geq 1 \tag{6}$$

where $p_c \in C_{\mathbf{B}l}(p)$, $N_h(p_c)$ is the set of neighborhood pixels for each pixel in $C_{\mathbf{B}l}(p)$, $|N_h(p_c)|$ refers to the cardinality of the set of neighborhood pixels, and ∇p is the minimum resolution step size of the image (usually $\nabla p = 1$). In other words, a pixel is said to be a boundary pixel if it has at least one off pixel (0 intensity) as a neighbor. We define the gradient magnitude at these boundary pixels $N_h(p_c)$ as

$$G_N(p_c) = |G_{Nx}| + |G_{Ny}|, \tag{7}$$

where

$$G_{Nx} = \frac{N_h(x_c+1, y_c) - N_h(x_c-1, y_c)}{2},$$

$$G_{Ny} = \frac{N_h(x_c, y_c+1) - N_h(x_c, y_c-1)}{2}$$

G_{Nx} and G_{Ny} correspond to the gradients in the x and y directions respectively.

Granulometry has traditionally been used in image processing to describe the size distribution of particles in an image [4]. We use granulometry to parameterize the level sets. This parameterization enables the extraction of significant level sets for segmentation. The parameter we use is cumulative gradient from level lines. This parameter is recorded for each level set.

We term this metric the Level Lines Gradient Granulometry (LLGG). The LLGG metric for a level set $\mathbf{B}_l$ is given by

$$\mathbf{L}_g(\mathbf{B}_l) = \sum_{c=1}^{cc} G_N(p_c) \tag{8}$$

where $G_N(p_c)$ is the cumulative level lines gradient of a connected component p_c and cc is the number of connected components in the level set $\mathbf{B}_l$ .The LLGG measure for a complete image is given by

$$\mathbf{L_g}(l) = \mathbf{L_g}(\mathbf{B}_{l\Delta b}) \quad (9)$$

where l is the level set number and usually ranges from 0 to G (maximum number of graylevels in the image (G=256 usually))in steps of Δb. Δb is a constant level step parameter (Δb =1 usually).

The LLGG metric at each level set is essentially the cumulative absolute gradient of the level lines in the level set. This metric tracks the behavior of the level lines across the level sets. The granulometry can be regarded as a 1-D signal whose peaks correspond to level sets containing important objects with strongly localized boundaries. We extract these peaks morphologically to eliminate redundancies between sampled level sets. This process is analogous to determining a non-uniform level step Δb.

Consider a 1-D LLGG signal $\mathbf{L_g}(B_l)$. Very closely separated peaks correspond to adjacent level sets with important information. To eliminate redundancy, we use only the strongest peak within a given neighborhood. Increasing the neighborhood size decreases the number of sampled level sets. This also decreases the computation time required in combinatorial analysis of the connected components collected from these non-linearly sampled level sets. Figure 4 illustrates the concept of the LLGG.

From the reduced set of level sets, a combinatorial analysis of the sampled level sets based on minimal total internal variance and maximal edge localization yields a segmentation. Figure 5 shows a sample segmentation result.

The proposed segmentation algorithm has been integrated into a CBR framework [6]. Segment specific features corresponding to color, texture and shape have been in performing segment-to-segment matching in an image database.

4. Conclusions

An automated approach to segmentation has been proposed using level set decompositions. The approach uses both textural and scale information. The solution is based on the analysis of connected components in a scaled Gabor decomposition. A level lines metric is utilized to decrease the computational complexity of the algorithm and to extract well-localized objects. The segmentation technique, in conjunction with relevant feature extraction and matching strategies, provides a vehicle for segment-based CBR. Currently, we are examining effective methods of algorithm validation for segmentation in CBR.

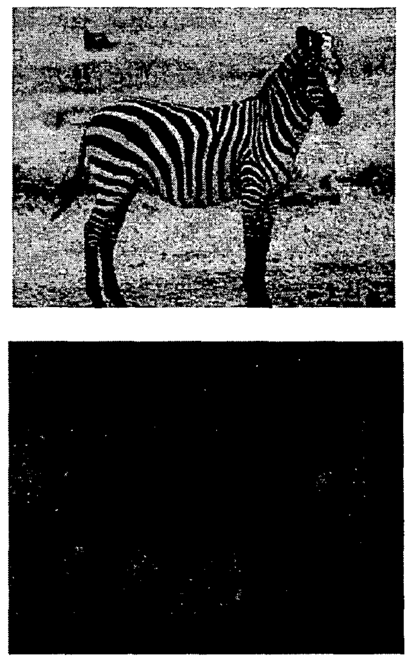

Figure 1. An image and its Gabor response at u=0.03 cycles/pixel, v=0.02 cycles/pixel.

Figure 2. Scaled Gabor response(wrt fig. 1)

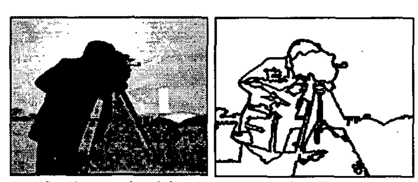

Figure 3. A scaled image and its important level lines

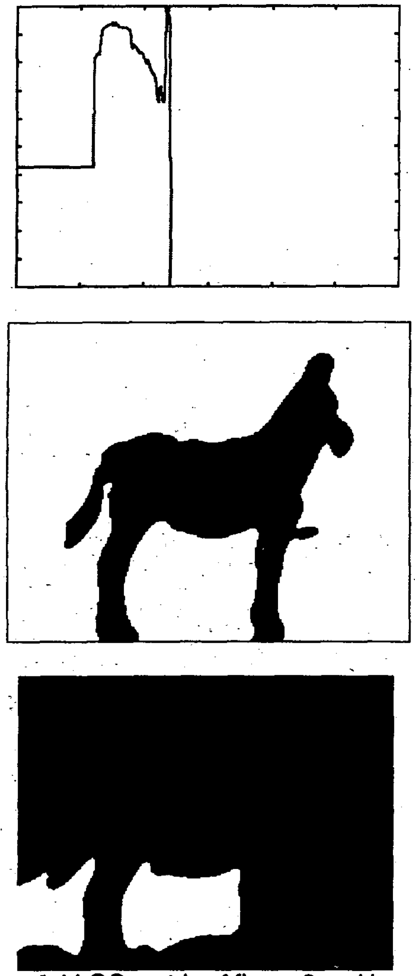

Figure 4. LLGG metric of figure 2 and level sets corresponding to peaks.

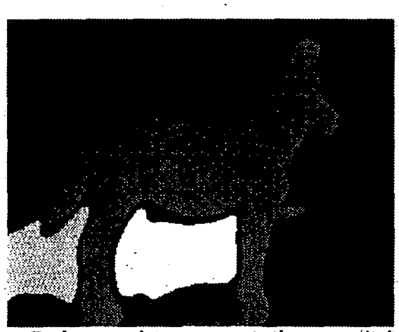

Figure 5. A sample segmentation result (wrt figure 1)

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