AREA MORPHOLOGICAL SEGMENTATION FOR CONTENT BASED RETRIEVAL

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ABSTRACT

Content based retrieval (CBR) has emerged as a useful tool for management of digital image libraries. Traditional approaches based on metadata and global features are limited in effectiveness and suffer from various drawbacks involving the use of heuristics and postprocessing techniques. The automated segmentation technique presented here is based on fuzzy clustering in a scaled texture space, which is generated via a bank of Gabor filters. Within the texture space, we scale the responses using the novel tool of area morphology. The segmentation algorithm provides segments satisfying a minimum scale requirement for use in CBR. The experiments indicate that our segmentation mechanism increases feature relevancy and reduces the computational costs of segment based matching.

1. INTRODUCTION

Increases in communication bandwidth, information content, and the size of multimedia databases have given rise to the concept of content based retrieval (CBR). CBR tools have shown increasing promise for the management of databases involving diverse applications such as automated inspection [8] and web-based searches [6]. Traditional methods of access and management have utilized text header information or metadata. Because the metadata are typically generated manually by a human operator, this approach has limited efficacy for large, rapidly changing databases.

In this paper we present a scalable segmentation technique for CBR. This approach involves clustering in a multi-dimensional space that encapsulates scaled texture information. Scaling is achieved by the novel area morphology technique, which manipulates connected components within image level sets according to their area. Comparisons to other scaling methods are shown to emphasize the importance of a scalable segmentation for CBR. In our approach, color, texture, and shape features are computed for each image segment. The resultant segmentations are utilized in a prototypical CBR engine for segment based matching.

2. SEGMENTATION

Conventional scale-space segmentations techniques rely purely on intensity/color information. Such an approach would have obvious shortcomings for images rich in texture information. Our CBR approach is based on the assumption that an image can be partitioned into segments that are homogeneous in terms of texture and/or intensity/color at a given scale. To extract texture information, we use a Gabor filterbank. Gabor filters have proven useful for texture extraction, as the filters optimize the tradeoff between localization in the spatial and frequency domains [4]. Furthermore, the Gabor filters are known to mimic the biological perception of texture [4].

A bank of Gabor filters is used here to compute a *texture space*, which is used for the dual purpose of texture feature extraction and segmentation. A 2-D Gabor function is a complex sinusoidal grating modulated by a 2-D Gaussian function:

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

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

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 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. Textures at different orientations and frequencies can be extracted by means of a number of Gabor filters tuned at different frequencies and orientations. These frequencies and orientations can be specified in terms of the Gabor half-peak frequency and orientation bandwidths [4].

The goal of the segmentation is to obtain segments homogeneous in terms of texture and intensity/color, while complying with a minimum scale requirement. Our solution is to cluster vectors within scaled versions of the texture space images. The criteria for the scaling technique are edge localization and the elimination of sub-scale objects. In terms of the connected components within the image level sets, the area open-close (AOC) filter provides the optimal scaling solution for both edge preservation and eradication of objects below the scale of interest. We compare the performance of the AOC filter with that of two other nonlinear filters, the 2-D median filter and the weighted majority with minimum range (WMMR) filter.

2.1. Area Morphology

Level sets are derived from thresholded representations of the original image. The level set parameters range from 0 to g-1 (where g=maximum number of graylevels in the image). The AOC operation [11] can be used to remove connected components within the image level sets that do not meet the specified minimum area. In this CBR application, the minimum area depends on the image granulometry. For a level set **B**, we can define the area open operation by

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

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 scale/area. This implies that $(x, y) \notin \overset{s}{\circ}(\mathbf{B})$ if $|\mathbf{C_B}((x, y))| < s$. The area close operation is similarly constructed, using instead the Boolean 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. A fast algorithm for area open is adapted here for area open/close. Recent advances in area morphology [1], [9] have introduced fast algorithms. 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

We apply a structuring element $\mathbf{K}$ of total size of a, to the original image $\mathbf{I}$. This ensures elimination of sub-scale connected components. Thus, the marker image is defined by

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

In this case, a is the minimum area/scale parameter. This marker image is used as a precursor to the reconstruction process discussed in Section 2.1.2.

2.1.2. Reconstruction by geodesic dilation

The 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 conditionally dilating these components one pixel at a time. Essentially, 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

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

where $\mathbf{R}_0 = \mathbf{M}$, and K^+ is a 3x3 cross-shaped structuring element. The above equation converges when reconstruction is complete. Let T be the number of updates required for complete reconstruction of a connected component. T is bound by the maximum geodesic distance between a boundary pixel of a connected component in $\mathbf{M}$ and the boundary in the reconstructed connected component in $\mathbf{R}$ [1].

Because the AOC is a connected-invariant filter, the operation either entirely removes or preserves an individual connected component in an image level set. For this reason, the level lines (edges of connected components) are not distorted in processing, as with the traditional morphological filters. Moreover, the AOC filter guarantees the removal of connected components beneath the minimum area. Various researchers have shown in the literature the attractive properties of the area morphological filters [2], [9], [11]. These include feature causality, Euclidean invariance, and edge preservation through scale. For these reasons, the AOC is optimally-suited to our scaling task in CBR.

Another nonlinear filter that flattens image regions and preserves edges is the median filter [3]. In the 1-D case, the median filter provides locally monotonic root signals – plateaus of a specified scale separated by ramp transitions. In the 2-D case, the ramp edges create difficulties in segmentation for CBR, because the ramps are often classified as separate segments, leading to over-segmentation and region distortion.

Perhaps a better choice for scaling in CBR is the weighted majority with minimum range (WMMR) filter [3]. This order statistic filter first finds the set of samples in a rank-ordered neighborhood with minimum range, and then computes the median (or other statistic) of this reduced set. Typically sets of m+1 samples with minimum range are used within windows of 2m+1 samples. Unlike the median filter that gives locally monotonic signals, the WMMR yields piecewise constant signals. So, the WMMR filter avoids the transition regions that plague the median. Nevertheless, in the 2-D WMMR case, we cannot exactly specify the minimum scale of the connected regions within the resultant image and edge distortion can occur. Figure 1 shows some experimental scaling results using the AOC, median, and WMMR filters.

2.2. Fuzzy clustering in scaled texture space

The segmentation for CBR is obtained by fuzzy clustering through the AOC-scaled texture space. For each position (x, y) in the input image, and each texture layer t, we have vectors $I(x, y, t)$ that are clustered using the multi-scale fuzzy c-means (FCM) algorithm [2]. The FCM-generated segmentations give regions that are homogeneous in terms of texture and are significant in terms of scale. Figure 2 shows some typical clustering results. It can be noticed that due to the staircasing effect of the AOC, a few undesirable segments that do not correspond to semantically meaningful regions are present. These are treated as connected components at a particular level-set and removed by a similar AOC operation with the same object-scale specified above. Figure 2 shows clustering results for different scaling methodologies.

Figure 3 shows the superiority of the AOC scaling technique over the median and WMMR scaling techniques, via a *level lines gradient granulometry* (LLGG) metric computed for the various scaling methods (Figure 2). The LLGG metric is computed by summing the gradient magnitude in the original image under the level lines (edges of connected components). The LLGG metric can be considered as a measure of the edge localization. Figure 4 shows the final segmentation results for two images in the database.

3. FEATURE EXTRACTION

3.1. Global Features

We utilize global image features to limit our initial search space in CBR. The two global features computed here pertain to color and texture. The global color feature is an estimate of the color probability density function (pdf) of the coarsely quantized image. This coarse color quantization is obtained in the prefiltered RGB image space. The prefiltering technique used for the purposes of smoothing and noise reduction is based on an integrated morphological, multispectral anisotropic diffusion process [10], [7]. This smoothing technique provides entropy reduction and impulse noise elimination, without the distortion of color. The coarse quantization is obtained by clustering in the prefiltered RGB space. The number of clusters computed is equal to the number of clusters used in the segmentation process. Figure 5 shows some preliminary results of the global coarse color quantization. The texture space obtained from the Gabor filterbank is also used for the purpose of extracting global texture features. Among the different global texture features estimated are total energy and mean/standard deviation of Gabor filter responses.

3.2. Local Features

The segmentation obtained from clustering the AOC-filtered Gabor responses is used for the purpose of extracting local features, which are segment-specific. These features include estimates of segment color, texture and shape. The local color feature is a segment specific color (estimated) probability density function. This pdf allows for finer discrimination of image segment content. The shape features are based on Fourier shape descriptors [5], which uniquely describe the segment shape and are invariant to translation, scaling, rotation and shearing. The scaled texture space is used for the purpose of extracting segment specific texture features. Since the segmentation is based upon the partitioning of the image into homogeneous regions of texture and color/intensity, we are able to compute segment-specific texture features. Among the different segment-specific texture features estimated are energy, mean and standard deviation (for each Gabor filter response).

4. QUERY PROCESSING AND MATCHING

In the CBR system, the query processing and similarity computation are performed online, while the segmentation and feature extraction are done off-line as the images are ingested into the database. Matching strategies for CBR are an evolving area of research in view of the diverse features involved. We use a hierarchical method to compute feature similarity in an intelligent manner. This method essentially trims down the initial search space by use of the global features. A cutoff (tolerance factor) is imposed on these results and the remaining matches are input to the next stage of matching. In the second stage of matching, color and texture features on a segment-by-segment are used to refine the ordering of potential matches. The AOC scaling methodology decreases matching costs by providing segments of a minimum scale, while the median and WMMR techniques do not necessarily guarantee minimum scale segments (numerous spurious segments are generated). Figure 6 shows an experimental CBR result. Our empirical results are based on the QBIC and Corel image databases. The databases used consist predominantly of flower images.

5. CONCLUSIONS

A scalable segmentation technique for CBR has been demonstrated. The solution is based on clustering texture features vectors within a scaled texture space. The scaling operation is accomplished by the area open-close filter. Similarity metrics for CBR is an important research issue given the diverse nature of features involved. As part of this we are investigating one-to-many and many-to-many segment matching strategies. A segment-based CBR is the first step towards realizing a well-motivated CBR system. The segmentation technique, in conjunction with relevant feature extraction and matching strategies, provides a versatile CBR prototype for investigating applications such as digital mammography and e-commerce.

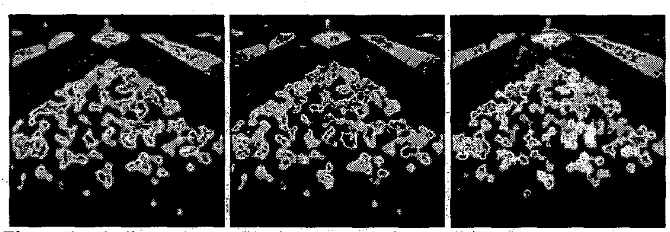

Figure 1. Median, WMMR and AOC scaled representations (7 x 7, $a = 49$)

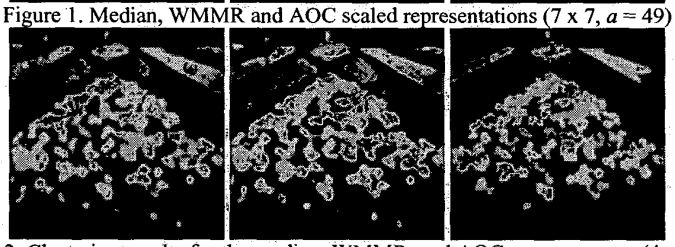

Figure 2. Clustering results for the median, WMMR, and AOC texture spaces (4 classes)

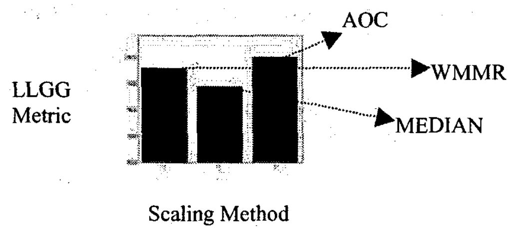

Figure 3. Superiority of AOC over WMMR and MEDIAN filters via the LLGG metric computed over the various (scaling techniques) segmentations(Figure 2).

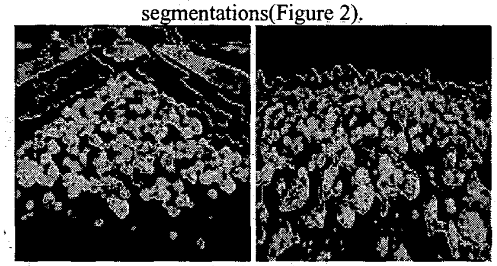

Figure 4. Segmentation results from the AOC-scaled texture space

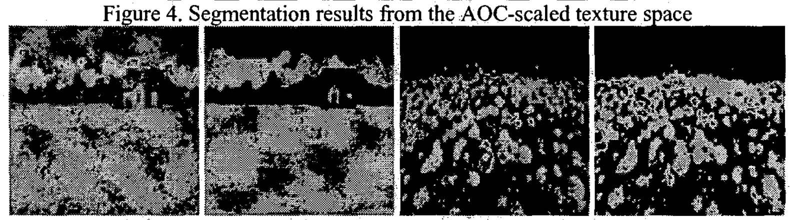

Figure 5. Examples of global coarse color quantization

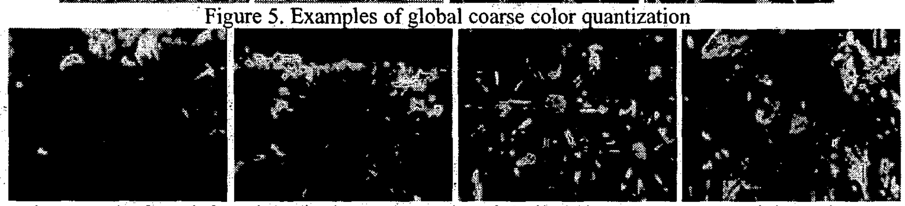

Figure 6. Query and top results from left to right (in decreasing order of similarity), Primary stage: Global color + texture sieve filter Secondary Stage: Local color +texture features

6. REFERENCES

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