ADAPTIVE COLOR IMAGE SEGMENTATION USING MARKOV RANDOM FIELDS

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ABSTRACT

A new framework for color image segmentation is introduced generalizing the concepts of point-based and spatially-based methods. This framework is based on Markov Random Fields using a Continuous Gibbs Sampler. The Markov Random Fields approach allows for a rigorous computational framework where local and global spatial constraints can be globally optimized. Using a Continuous Gibbs Sampler enables the algorithm to adapt continuous-valued regional prototypes in a manner analogous to vector quantization while the discrete Gibbs Sampler is used to adjust region boundaries.

1. INTRODUCTION

In computer vision, several steps are needed to understand an image or some portion of it. A critical step is image segmentation. Image segmentation can be subdivided into three broad categories: point-based techniques [7], spatially- or region-based methods [6] and hybrids [2, 9].

Point-based methods act only on single pixels and do not take spatial information into consideration. They are usually set up to minimize the mean squared error or other quantity [1]. This is usually done using vector quantization (VQ) or some type of energy minimization such as Bayes [1, 9] or Minimum Description Length [1]. VQ has many forms and depending on the end application different algorithms have been developed. Some of the better known are the k-means [1] and mixture of principal components algorithms [7] (vector angle is used as similarity criterion instead of Euclidean distance). The primary drawback of point-based techniques is their inability to take into account local variation to avoid the formation of many small extraneous regions.

Region-based methods are spatially based and locally optimized [6]. Usually, no global information is used to obtain a result which means that many small regions may proliferate in areas of high texture and a region could include two vastly different color regions due to a small gradient between the two distinct colored regions. This is a causal method in that every included pixel is related to the previously included pixels.

Hybrids of point-based and region-based methods include Markov Random Fields [2, 3], region competition [9]. Markov Random Field-based methods and region competition try to achieve image segmentation by minimizing local error and maximizing regional differences. The Both approaches are considered "a-causal" in that decisions to include a pixel in a region are independent of the order in which they were visited. In MRF-based solutions, edges and textures can be modelled directly in the image segmentation process [3, 8] which makes this framework desirable for further development.

Color is a very important visual quality for human perception. Many objects cannot be correctly identified without analyzing their color. Therefore, this paper builds on previous work in color image segmentation using Markov Random Fields (MRF) [2] and extends it to an adaptive prototype-based MRF framework. The main motivation for doing this is to be able to overcome any initialization errors. The region prototypes will be adjusted in the MRF framework using Continuous Gibbs Sampling. Preliminary experimental results are presented and discussed.

2. MARKOV RANDOM FIELDS

The modeling problems in this paper are addressed from the computational viewpoint by using Markov random fields to model the image segmentation process. There are two primary concerns: how to define an objective function for the optimal solution of the image segmentation problem, and how to find its optimal solution. It is reasonable to define the desired solution in an optimization sense given the various uncertainties in the imaging process. In this case, the solution to our segmentation problem would be interpreted as the optimum solution to the optimization objective.

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Gibbs Random Fields (GRFs) [3, 8] provide a natural way of modeling context dependencies between, for example, image pixels of correlated local features [4]. One of the motivating developments is the improved insight and available methods for Gibbs sampling (discrete and continuous) and Simulated Annealing.

We propose to define the spatial context using a Gibbs/Markov approach. Certainly others have used Markov random fields for image segmentation [4, 8]; however, normally these methods involve Gauss-Markov random fields, where the GMRF defines a spatial texture, from which segmentation can proceed as a separate hypothesis-testing procedure applied to the GMRF likelihood [4]. Our approach is quite different: we wish to find the segmented image directly as the result of energy minimization of some appropriately-defined Gibbs random field. Furthermore the regions are not distinguished on the basis of texture, rather on intensity differences (whether in one or more dimensions).

The formulation of our Gibbs model will be similar to others used for segmentation [3, 4] except that we consider global constraints in addition to local ones used in classic MRF research. We demonstrate the advantages of constructing an energy function for Markov Random Field-driven color image segmentation using these global constraints.

The MRF-based segmentation model is defined by the contextual relationships within the local neighborhood structure. Since our goal is the assertion of local constraints, rather than an accurate modeling of spatial textures [4], we shall only be concerned with first order random fields, both simplifying the model and limiting the computational complexity.

It has been shown that color images can be highlight invariant using the following transformation [5, 7]:

$$\vec{c}^{\prime}_{i,j} \quad = \quad \vec{c}_{i,j} - AVG \qquad (1)$$

where $\vec{c}_{i,j}$ represents a pixel vector (in this case composed of the three RGB values), $\vec{c}^{\prime}_{i,j}$ is the highlight invariant color vector and AVG denotes the average value of the elements of a single pixel - in this paper these are R, G and B. The average for each pixel is calculated based only on the individual elements of that pixel. The vector angle and inner vector product have been shown to be shading invariant distance measures [7]. This concept was further extended to a Markov Random Field framework [2]. This framework with respect to global constraints will be now summarized.

Suppose we are given a color image on a pixel lattice $\mathcal{L} = \{i, j\}$. Each pixel $\{RGB\}_{i,j}$ is transformed to its normalized representation $\vec{c}^{\prime}_{i,j}$ using (1).

The primary drawback with strictly local, pixel-neighbor models is that they suffer from the same problems as other region-growing approaches [2]. For example, two vastly differently colored pixels may be grouped into a single region if they are linked by noisy or intermediately-colored pixels. A global model is necessary to overcome drawbacks of local models. If we associate with label l (each pixel (i, j) is assigned an integer label $0 \leq l(i, j) < N$ to associate it with a region color) a global transformed color $\{\vec{a}_l\}$ then each region is forced to be well defined:

$$H[\{l(i,j), \vec{a}_l\}] = \sum_{i,j} \Omega(\theta_{\vec{a}_{l(i,j)}, \vec{c}^{\prime}_{i,j}})^2 + \beta\left[(1 - \delta_{l(i,j), l(i,j+1)}) + (1 - \delta_{l(i,j), l(i,j+1)})\right] \qquad (2)$$

where β controls the relative constraints on the degree of region cohesion and fragmentation, while $\delta_{l(i,j),l(i,j+1)}$ is 1 when both labels are the same and 0 otherwise. The region colors $\{\vec{a}_l\}$ were originally fixed [2]; that is, the sampling and annealing took place only over the label indices $\{l(i, j)\}$ themselves. The $\{\vec{a}_l\}$ were found by a preceding step, such as vector quantization [7]. However, in this paper as mentioned earlier this assumption will not be made and the region colors $\{\vec{a}_l\}$ will be allowed to adapt; in other words, the sampling and annealing will take place not only over label indices $\{l(i, j)\}$, but also over the region colors $\{\vec{a}_l\}$. This will allow for the correction of errors done by vector qunatization or other initialization algorithms.

Finally, the degree to which the region color is to be asserted at each pixel should be spatially-varying, now for two reasons. First, the color-dependent effect of noise, particularly for dark and highlight pixels.

Second, we are normally not interested in pixels in regions of high color gradient; at the very least, these pixels should not unduly influence the Gibbs energy by being inconsistent with the region color $\{\vec{a}_l\}$.

If we let [2]

$$u_{i,j} = \min\left\{\frac{1}{\mathrm{var}(\Omega(\theta_{\vec{c}^{\prime}_{i,j}, \vec{c}^{\prime}_{i+1,j}}))}, \frac{1}{\mathrm{var}_{\mathcal{N}}(\Omega(\theta_{\vec{c}^{\prime}_{i,j}, \vec{c}^{\prime}_{i+1,j}}))}\right\} \qquad (3)$$

that is, the first variance is a point-wise one (based on a noise model) and the second is a spatial one (computed over a local neighborhood $\mathcal{N}$), then our segmentation model becomes

$$H[\{l(i,j), \vec{a}_l\}] = \sum_{i,j} u_{i,j}\Omega(\theta_{\vec{a}_{l(i,j)}, \vec{c}^{\prime}_{i,j}})^2 + \beta\left[(1 - \delta_{l(i,j), l(i,j+1)}) + (1 - \delta_{l(i,j), l(i,j+1)})\right] \qquad (4)$$

This gives us a concise and coherent representation of the color image segmentation problem by incorporating both local and global constraints. The global constraints are defined by global color region labels obtained through some vector quantization process such as the one presented in [7]. Local constraints are included by virtue of using pixel level constraints in the MRF model.

Model (4) is a trade-off between a completely local region growing approach, where many spurious regions can be created, and a global color clustering approach where regions of differing color can be inadvertently merged. Furthermore, the use of vector angle accuracy weights (3) allows the less reliable calculation of vector angle for small highlight-invariant values (cf. (1)) to be appropriately modulated.

3. CONTINUOUS GIBBS SAMPLING

For the region colors $\{\vec{a}_l\}$ in models (2) and (4) to adapt, the sampling and annealing has to take place over the region colors. Since region colors are inherently continuous values (not discrete values like the region labels), the operations have to be done in the continuous domain using the continuous Gibbs sampler.

Let's recall that the Gibbs distribution is written as:

$$\pi(\Omega) = e^{-H(\Omega)/T}/Z \tag{5}$$

where $H(\Omega)$ is the energy being minimized, T is the temperature and the partition function Z is defined as

$$Z = \sum_{\Omega} e^{-H(\Omega)/T} \tag{6}$$

Calculating Z can be a very difficult problem especially for large spaces [3, 4]. However, in the continuous case, the problem becomes even more difficult as the summation changes to an integral.

Carrying out this integral is generally intractable. However, it is possible to compute the conditional probability of a particular MRF configuration by quantizing the Gibbs distribution space. Therefore, probabilities for all quantized values of $\{\vec{a}_l\}$ are calculated for a particular energy configuration. This is done first by evaluating $e^{-H(\Omega)/T}$ for all possible quantizations of Ω. Next, the integral corresponding to (6) is computed numerically using the previous results. The probabilities (5) can now be calculated. Thus, the obtained probability distribution function can be used to find the conditional distribution function from which we can obtain a sample. This conditional distribution function needs to be recalculated for every pixel at every iteration. Drawing samples from the conditional distribution function of the Gibbs distribution implements the continuous Gibbs sampler.

The general color image segmentation algorithm is now described:

- All pixel labels are randomly initialized
- Region colors $\{\vec{a}_l\}$ are initialized to some vector quantized values using (1) and the Mixture of Principal Components algorithm [7]
- Repeat for several iterations:
  - At each pixel in the image until a minimum is reached:
    - Minimize the energy in models (2) or (4) by sampling labels using the discrete Gibbs sampler [3]
    - Draw a sample from the conditional Gibbs distribution (i.e., what we described as continuous Gibbs sampling) for annealing the region colors
  - Lower the temperature T

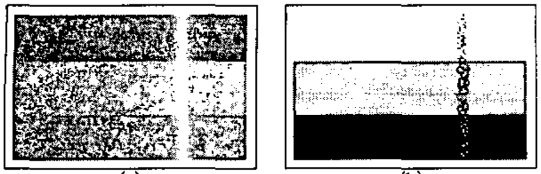
If the temperature reduction occurs slowly enough, this annealing process should converge in probability to the global minimum [3]. However, applying simulated annealing to the usual 256 quantization levels present in grayscale images and 256^3 levels in color RGB images is computationally prohibitive (in the case of $R'G'B'$ this would be approximately 512^3 because of the negative and positive coordinates). Therefore, the region color associated with a particular label is obtained by drawing a sample from the distribution representing all the pixels that have this label. A practical implementation would only require that potential color regions be sampled from pixel vectors associated with that region label. Although this does not allow the use of intermediate or interpolated pixel values for color regions, in practice this is not necessary as we are trying to identify homogenous color regions.

4. RESULTS

The Gibbs Sampler [3] was used to optimize both (2) and (4) in their fixed and adaptive forms. For the fixed global model (4) the label colors $\vec{a}$ are determined using the algorithm presented in [7]. For the adaptive global model, the initial prototypes are of course selected randomly.

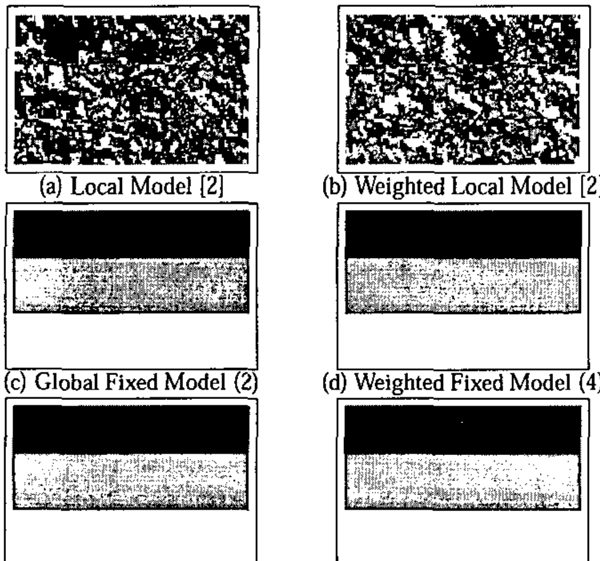
Results were prepared an artificial image of colored bands, shown in Figure 1 respectively. The artificial image varies in intensity horizontally (i.e., from left to right and a saturated highlight is present near the right border). Some additive uniform uniformly distributed noise was added to this image.

The MPC result on the artificial image is shown in Figure 1(b). The highlight part is clearly a mixture of the three other segmentation classes due to having a nearly null vector representation in the R', G', B' space, and the absence of spatial constraints prevents the ambiguity from being corrected. For the MRF models, the results in Figure 2(a) and Figure 2(b) clearly illustrate the problems of boundary length discussed in [2], because of the lack of region-defining constraints such as characteristic region vector. Figure 2(c) demonstrates the type of result that is obtained



(a) (b)

Fig. 1. Color band image: (a) Original, (b) MPC segmentation.



(a) Local Model [2] (b) Weighted Local Model [2]

(c) Global Fixed Model (2) (d) Weighted Fixed Model (4)

(e) Global Adaptive Model (2) (e) Weighted Adaptive Model (4)

Fig. 2. Color Band image: Results of two proposed MRF models compared with previous results.

using Model (2). As desired, no highlight parts remain as these areas have been subsumed into their adjacent regions.

Figure 2(d) shows the results for the same color bands, but now the vector angle calculation is weighted in terms of the accuracy to which to the angle can be determined (which is affected by darkness or degree of highlight), as in (4). The main difference between models (2) and (4) seems to be the faster speed of convergence of the latter over the former (for the example image presented).

Similar results are obtained for the adaptive prototype case and are shown in Figure 2(e) and (f). The main difference between these results and the previous ones was that the adaptive models were initialized using a random set of prototypes. The adaptive models ran for approximately the same number of iterations on average as the fixed models. However, each iteration (i.e., cycle through all points in the image) was considerably more computationally intensive in the adaptive model case.

5. CONCLUSIONS

A new framework for adaptive color image segmentation using Markov Random Fields and continuous Gibbs sampling has been presented. The new method presents several advantages: adaptability of global constraints (region colors) to the data, sampling over both region labels and region colors using the Gibbs sampler (both discrete and continuous), optimization of local contextual constraints (taking into account local features) with a global energy function (making sure that regions are optimally segmented with respect to each other). Hybrid methods have been introduced recently including region computation. However, none of these methods provides a framework as flexible as MRFs which not only adaptively and globally optimizes local constraints, but can also easily integrate texture handling and edge detection (line processes) within the segmentation process.

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