Image Segmentation using a Genetic Algorithm and Hierarchical Local Search

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Motivation

- Image segmentation important in image processing.
  - Often used as a preliminary step.
  - Can emphasize boundaries between objects.
  - Locate distinct objects in images.
- Image segmentation is challenging
  - Difficult to succeed across diverse images.
  - Even a relatively small image has a large number of points.
  - Large number of locally optimal segmentations.
  - Ideally want it done automatically.
- The purpose of this paper
  - Use Potts spin glass model to define image segmentation as optimization problem.
  - Use a steady-state genetic algorithm with hierarchical local search to solve the problem.

Outline

- Image segmentation as Potts spin glass.
- Algorithm
  - Steady-state genetic algorithm.
  - Crossover operator.
  - Hierarchical local search.
- Experiments.
- Conclusions and future work.

q-state Potts Model

- Origin in physics.
- Spins arranged on a 2D or 3D lattice.
- Each spin s_j can have up to q states.
- Edges have weights that define relationships between neighboring spins.
- Energy defined as

$$E = -\sum_{\langle i,j \rangle} J_{i,j}\delta(s_i, s_j) \ ,$$

  where $\delta(s_i, s_j) = 1$ if $s_i = s_j$, and $\delta(s_i, s_j) = 0$ if $s_i \neq s_j$.
- Usual task is to minimize the total energy of the system.
- To minimize energy, neighboring spins s_i and s_j should be equal if $J_{i,j} > 0$; otherwise the spins should be different (ideally). Larger $J_{i,j}$ values are more important than smaller.

Mapping Image Segmentation to Potts model

- Each pixel corresponds to one spin.
- The value of the spin defines the pixel's segment.
- Map grayscale image to a set of couplings $\{J_{i,j}\}$ between neighboring pixels:

$$J_{i,j} = 1 - \frac{\Delta_{i,j}}{\theta \Delta_{avg}},$$

where

  - $\Delta_{i,j}$ is absolute difference between neighbors,
  - Δ_{avg} is average difference between all neighbors in the image,
  - $\theta = 1$ controls sensitivity to changes in intensity.

- Small differences between neighbors imply a large coupling (meaning that the neighbors should be in the same segment).
- Large differences between neighbors imply a small coupling (meaning that the neighbors should be in different segments).

Mapping Image Segmentation to Potts model

- Image segmentation using Potts model
  - Number q of states in Potts model = number of segments.
  - Each pixel's state defines its segment.
  - Minimizing energy corresponds to segmentation so that similar neighbors belong to the same segment (and dissimilar neighbors belong to different segments).
- Can apply any optimizer (e.g. simple genetic algorithm).
- But naive implementations won't work too well
  - High dimensionality.
  - Large number of local optima.

Genetic Algorithm

- Representation
  - Segmentations represented by strings.
  - One character for each pixel in the image (long strings).
  - Each character can take q values (q=number of segments).
- Steady-state hybrid GA with small population.
  - Initial population of strings represents random segmentations.
  - Each iteration selects two random parents from population.
  - Parents are combined using crossover to create new string.
  - Local search used to improve the resulting string.
  - Candidate replaces the worst parent if it's better.

Algorithm

- Two details left to discuss:
  - Crossover operator.
  - Local search and hierarchical local search.

Crossover Operator

- Creates new segmentation c from segmentations a and b.
- Select randomly rectangular region.
- c takes content of rectangular region from a.
- c takes the rest from b.
- Selecting rectangular region
  - Picks a random pixel for center of region to swap.
  - Size of swap region for image of size $x \times y$ is $\sqrt{x/2} \times \sqrt{y/2}$.
  - Other scenarios possible.

Transforming Solutions for Crossover

- Similar segmentations have often different strings (renaming segments produces extremely different strings).

Image a

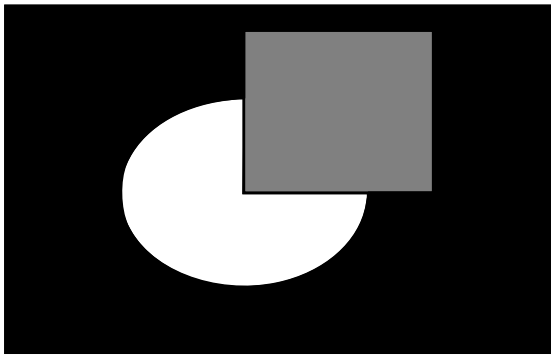
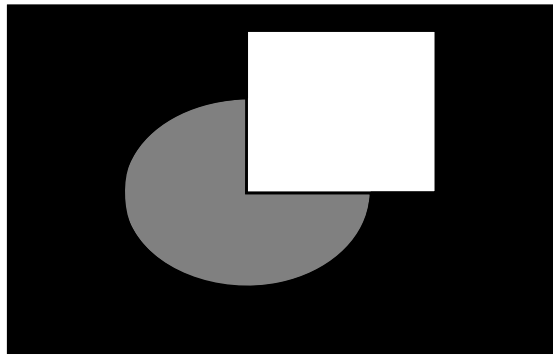


Image b



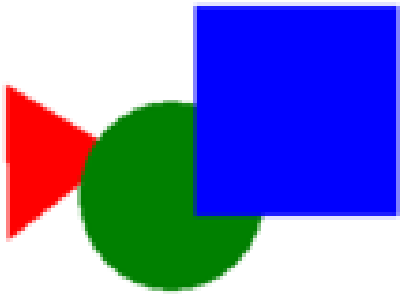
- Crossover without transforming parents leads to poor results because of excessive disruption and ineffective juxtaposition.
- Resolution: Transform parents by renumbering segments
  - Calculate conditional probabilities that a segment i in parent a is represented by segment j in parent b for all i and j.
  - Use greedy algorithm to renumber each segment in parent a to the most likely segment it represents in b.

Difficulties with Simple Local Search

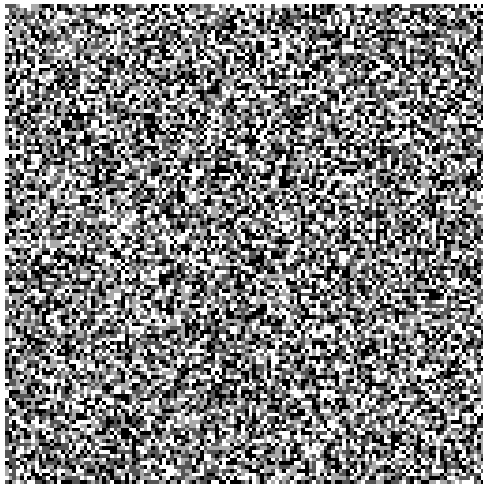
- Problems have large number of variables in each solution.
- Advantageous to use local search to speed optimization up.
- First attempted to use bit-flip hill climbing (HC)
  - Would get stuck at poor local optimum, even for images where each segment consisted of a single color (easy to segment).
  - Led to actual degradation of performance.

Difficulties with Simple Local Search: Illustration

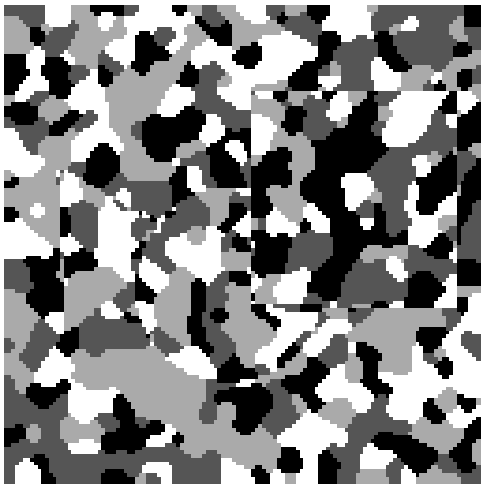
Initial image



Random segmentation



Segmentation after bit-flip HC

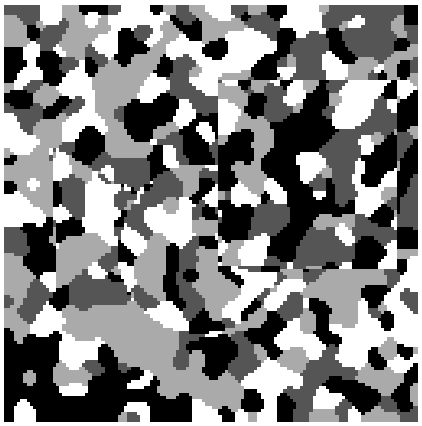


Hierarchical Local Search

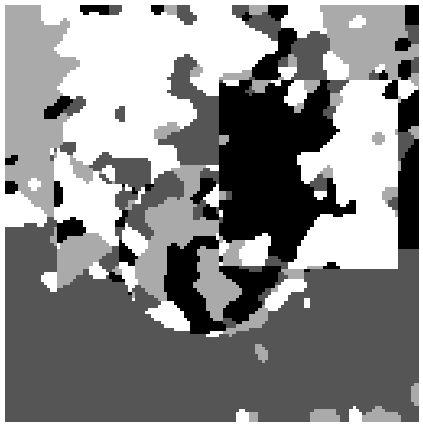
- Developed hierarchical local search to tackle this challenge.
- Start with simple bit-flip hill climbing.
- Treat each connected segment as one variable (character).
- Each iteration
  - Try to change each connected segment (connected region of pixels assigned 1 segment number) to another color.
  - Accept the best change (if improvement).
  - Terminate when no more improvement possible.
- Regions increase in size (regions merge over time).
- Implementation can be done efficiently.
- Important: Deals with the problem of simple HC, leading to a much more efficient search for good segmentations.

Steps of Hierarchical Local Search

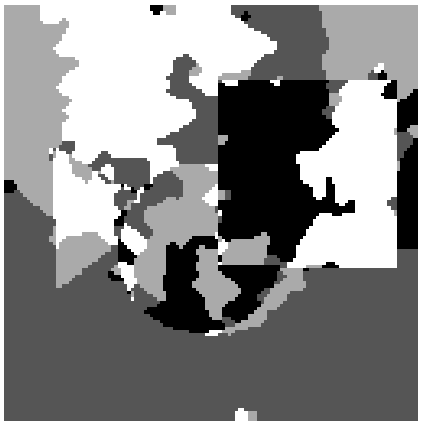
$Step = 1$



$Step = 50$



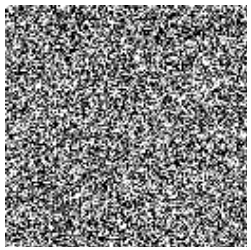
$Step = 100$



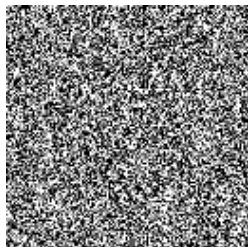
$Step = 143$

Demonstration of Importance of Hierarchical LS

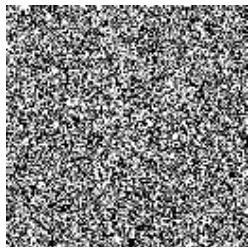
$g = 1$, no LS



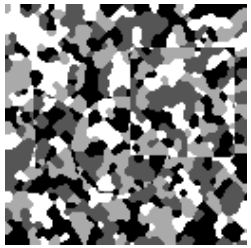
$g = 100$, no LS



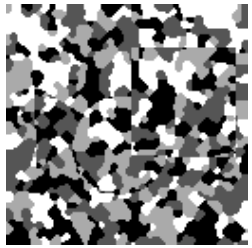
$g = 1000$, no LS



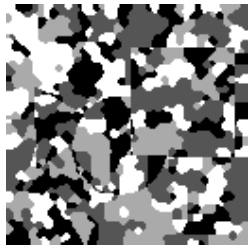
$g = 1$, DHC



$g = 100$, DHC



$g = 1000$, DHC



$g = 1$, HLS

$g = 100$, HLS

$g = 1000$, HLS

Experimental Setup

- Number of segments set to $q = 4$.
- Population size set to $N = 50$.
- Input images converted to 8-bit grayscale for 256 distinct gray levels before generating the weight matrix.
- Two different digital images were examined
  - House image of size 150×100 pixels.
  - Dog image of size 160×128 pixels.
- For each image:
  - Find final resulting segmented image using hybrid GA.
  - Examine image after coloring regions based on average color of that region in original image.
  - Compare the results to meanshift segmentation.

House Image using Hybrid GA

Initial image

Segmented image

Average color

House Image using Mean-Shift Segmentation

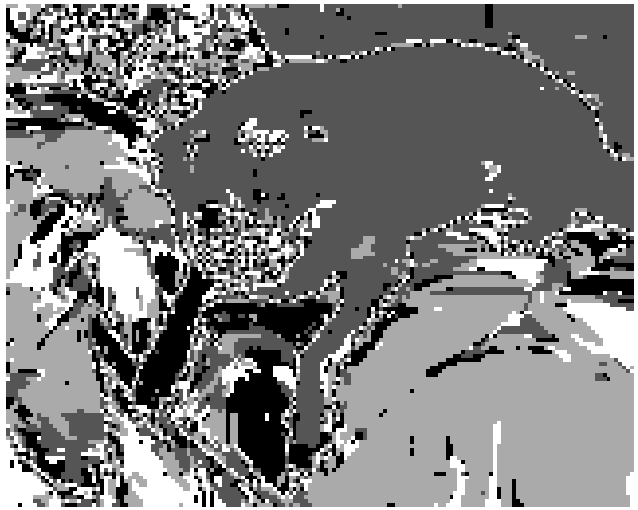
Intermediate

Final, 17 colors

Dog Image using Hybrid GA

Initial image

Segmented image



Average color

Dog Image using Mean-Shift Segmentation

Intermediate

Final, 26 colors

Conclusions

- Described a hybrid GA to perform image segmentation.
- Hierarchical local search proposed to improve efficiency.
- Transformation used to lower disruption due to crossover.
- Resulting hybrid GA was able to efficiently segment images.
- Results also show the necessity of hierarchical local search where simple bit-flip local search actually led to performance degradation.

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