A Graph-Based Memetic Approach to Sketch Geolocation

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Outline



Problem Overview

- Scene Matching based on Spatial Relations
- An Evolutionary Algorithm
 - Global Search Strategy
 - Local Search Strategy
 - Combined Memetic Approach
- Experimental Results
- Conclusions



- Scene Matching
 - Hand Drawn Sketch
 - Segmented Satellite Image







Combinatorial Optimization

Given a target sketch of objects,

$$\mathcal{X}_T = (o_1, \dots, o_N)$$

... and a set of reference objects,

$$\mathcal{X}_R = (x_1, \dots, x_M)$$

what is the set of objects from X_R that best matches X_T ?

$$\Gamma = \left(x_{(1)}, \dots, x_{(N)} \right)$$

- Constrained optimization
 - Solutions should be in a similar configuration
 - Object types should match (*e.g.* buildings, parking lots)

Representing Object Sets

- Object sets are represented as graphs
 - Vertices \rightarrow Objects
 - Edges \rightarrow Spatial relationships









- The histograms of forces (HoF) capture the relative spatial position between two objects
- A force histogram $F_r^{AB}(\theta)$ is a way of representing the degree of truth of the statement, "A is in direction θ from B."
 - r = 0 gives the histogram of constant forces
 - -r = 2 gives the histogram of gravitational forces



Attributed Relational Graphs

• We create attributed relational graphs (ARGs) for the target sketch and reference database





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- ARG similarity is computed as the average crosscorrelation of corresponding histograms
 - ARGs must be complete graphs of the same size
 - Object correspondence is defined by vertex order



Normalized Cross-Correlation:

$$\psi_{\rm CC}(F_r^{1i}, F_r^{2i}) = \frac{\sum_{\theta} F_r^{1i}(\theta) F_r^{2i}(\theta)}{\sqrt{\sum_{\theta} \left(F_r^{1i}(\theta)\right)^2} \sqrt{\sum_{\theta} \left(F_r^{2i}(\theta)\right)^2}}$$

 $\psi_{\text{Hist}}(h_{1i}, h_{2i}) = \frac{1}{2}\psi_{\text{CC}}(F_0^{1i}, F_0^{2i}) + \frac{1}{2}\psi_{\text{CC}}(F_2^{1i}, F_2^{2i})$



 F-Histograms need to be normalized to account for sketch rotation





 $d_{ij} = \varphi^{1i} - \varphi^{2i}$

$$\boldsymbol{D} = \left(d_1, \dots, d_{N(N-1)/2}\right)$$

Best rotation angle for the sketch:

$$\varphi^{\star} = \operatorname*{arg\,min}_{d_i \in \mathcal{D}} \left[\pi - \sum_{d_j \in \mathcal{D}} \left| \pi - \left| d_i - d_j \right| \right| \right]$$



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• Each histogram pair is weighted by how far the angular difference is from the optimal rotation angle



• Overall fitness of a solution G_{Γ} is given by its similarity to G_T

$$\Psi(G_{\Gamma}) = \frac{N(N-1)}{2} \sum_{i=1}^{N(N-1)/2} \psi_{\text{Trap}}(\varphi^* - d_i) \psi_{\text{Hist}}(h_{\Gamma i}, h_{Ti})$$



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An evolutionary framework maintains a population of chromosomes which could match the sketch





Build ARG





Compare with sketch ARG to compute fitness





Local Search Strategy





Exploration vs. Exploitation

- Traditional crossover and mutation tend to produce invalid solutions (graphs are incomplete)
- Exploration (Global search strategy)
 Handled by the random initialization operator
 - New random individuals are added every few generations
- Exploitation (Local search strategy)
 - Handled by the one-seed and VF2 local search operators
 - Good children replace their parents





- Create an initial population of random chromosomes
- While stopping criteria is not met
 - For each chromosome, generate children using local search (exploitation)
 - If a child is more fit than its parent, it replaces the parent
 - Every few generations, replace the lowest scoring fraction of the population with new random individuals (exploration)
- Return top scoring individuals from the last generation

One-Seed Set Reconstruction

 A single seed object is kept from the chromosome, and the remaining objects are chosen to give the best match with the sketch



Sketch

"Nearly correct" Chromosome

Local Search

VF2 Subgraph Isomorphism

• The VF2 algorithm is used to find the subgraph which most closely matches the sketch



Sketch

"Nearly correct" Chromosome

Local Search



One-Seed vs. VF2



- One-Seed
 - Moves slowly through the search space
 - Builds up partial solutions one object at a time
 - Complexity is $O(N^5K)$
 - N is sketch size and K is neighborhood size
- VF2
 - Searches the entire local neighborhood
 - Uses a state space representation and a set of feasibility rules to guide the search
 - Complexity
 - Best case is $O(N(K + N^2))$
 - Worst case is $O(K!(K + N^2))$



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Experiments

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- Hand-segmented database of Columbia, MO
 - 2467 buildings
 - 378 parking lots
- Reference ARG pre-computed with 50 nearest neighbors
- 100 target sketches randomly generated for each test configuration:
 - 4, 6, 8, 10, and 12 objects
 - Direct resubstitution sketches
 - Transformed sketches





Accuracy Results

Mutation Method	Objects in Sketch	Percent Correctly Matched	
		Direct Resubstitution	Transformed
		Sketches	Sketches
1-Seed	4	95.1%	80.6%
	6	98.5%	95.6%
	8	99.6%	93.4%
	10	94.8%	81.7%
	12	86.2%	87.2%
VF2	4	98.7%	80.4%
	6	96.6%	94.3%
	8	98.1%	86.0%
	10	90.8%	69.2%
	12	76.5%	78.8%







Average Runtime for Direct Resubstitution Sketches

Number of Objects in Sketch

Examples





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➤ Conclusions





- Scene matching is a real-world problem with intuitive global and local search paradigms
 - A memetic framework can help combine multiple search strategies
- Evolutionary computation helps manage complexity in large search spaces
- Further improvements to the algorithm
 - $-(\mu + \lambda)$ evolution strategy with appropriate diversity mechanisms
 - Tabu search to avoid researching regions



Thank You



