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Building Networks for Image Segmentation using Particle Competition and Cooperation

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Outline

- Particles Competition and Cooperation (PCC)
- Interactive Image Segmentation using PCC
- Proposed Approach
  - Network Index
- Computer Simulations
- Conclusions

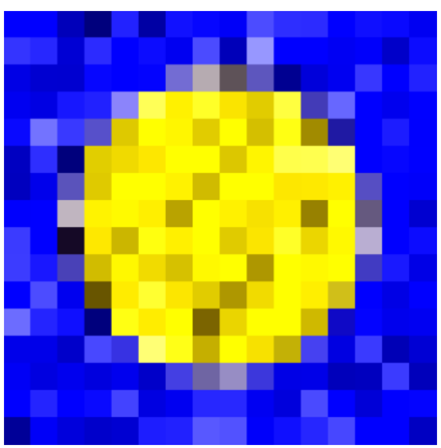
Particles Competition and Cooperation (PCC)

- Semi-Supervised Learning approach
  - Original PCC have particles walking in a graph built from vector-based data
  - Cooperation:
    - Particles from the same class (team) walk in the network cooperatively, propagating their labels.
    - **Goal**: Dominate as many nodes as possible.
  - Competition:
    - Particles from different classes (teams) compete against each other
    - **Goal**: Avoid invasion by other class particles in their territory

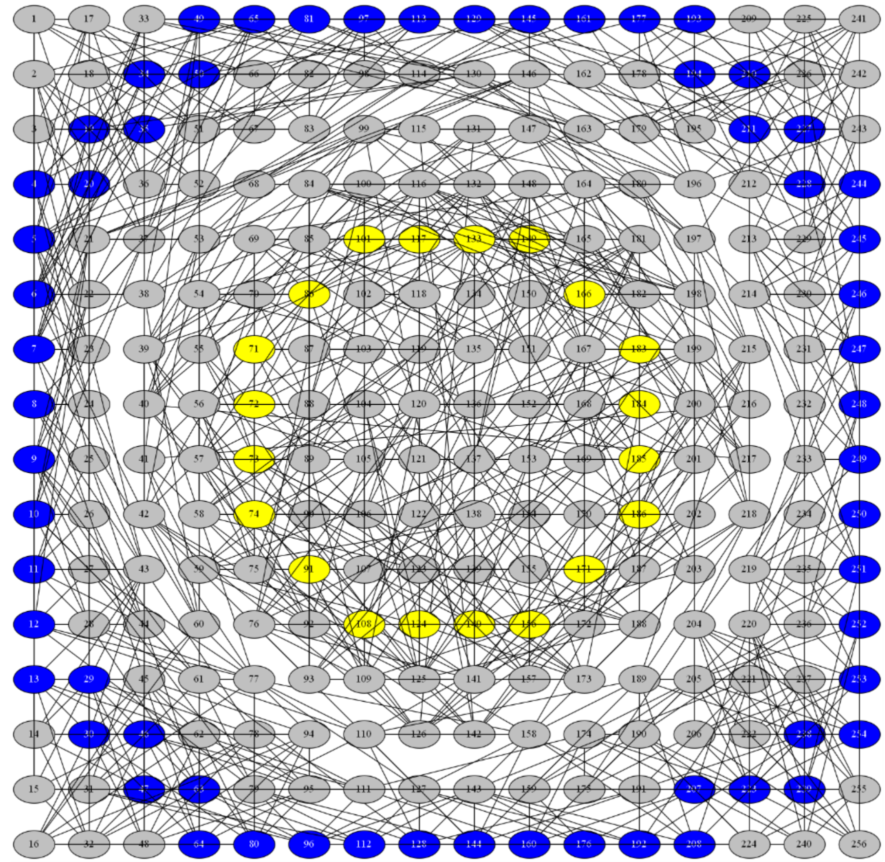
[13] Breve, F., Zhao, L., Quiles, M., Pedrycz, W., Liu, J.: Particle competition and cooperation in networks for semi-supervised learning. IEEE Trans. Knowl. Data Eng. 24(9), 1686–1698 (2012)

PCC for Interactive Image Segmentation

- An undirected and unweight graph is generated from the image
  - Each pixel becomes a graph node
  - Each node is connected to its k-nearest neighbors according to some pixel features.


(a)

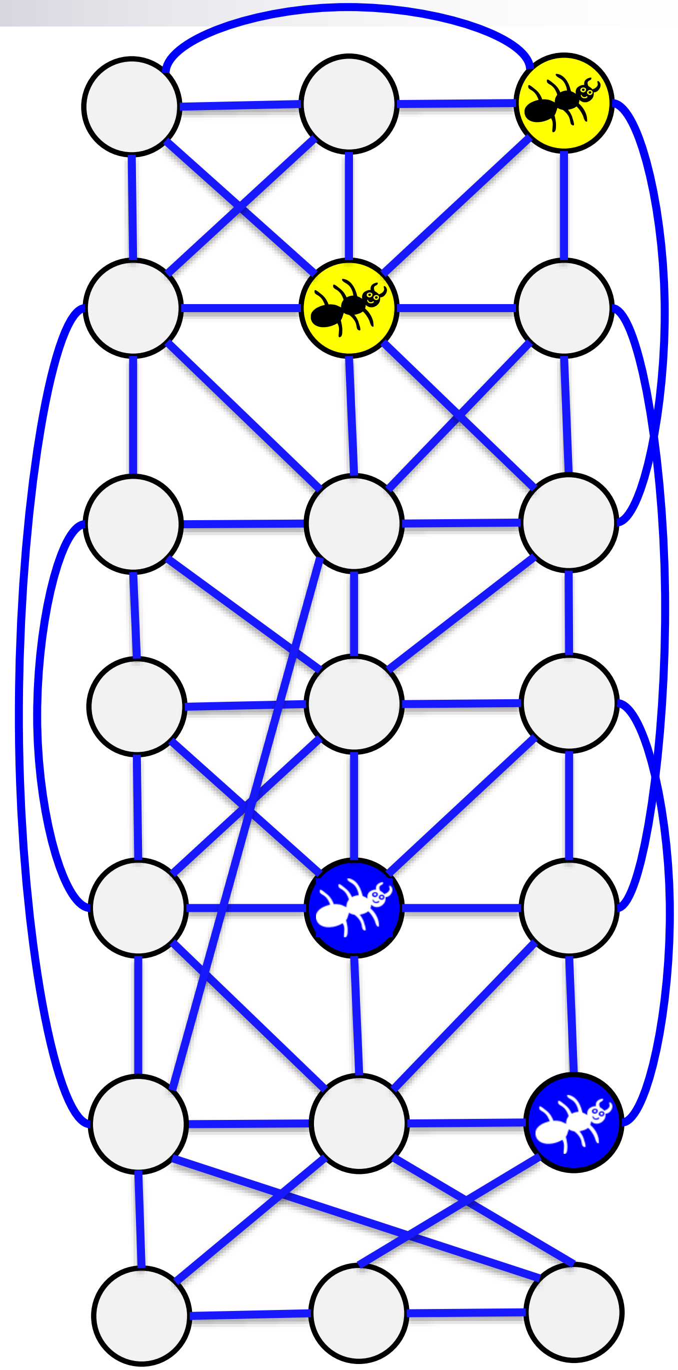

(b)


(c)

Proposed Method Segmentation Example: (a) original image to be segmented (16x16 pixels); (b) original image with user labeling (green and red traces); and (c) graph generated after the original image, where each image pixel corresponds to a graph node. Labeled nodes are colored blue and yellow, and unlabeled nodes are colored grey. Each labeled node will have a particle assigned to it.

PCC for Interactive Image Segmentation

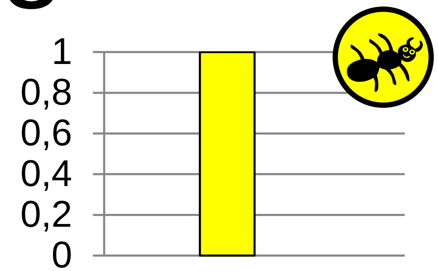
- A particle is generated for each labeled node
- Particles initial positions are set to their corresponding nodes
- Particles with same label play for the same team



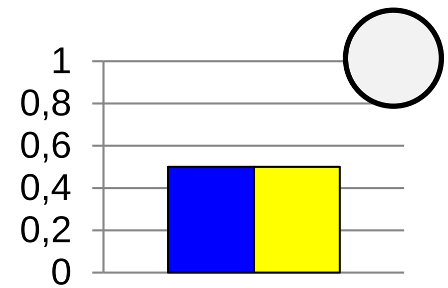
[5] Breve, F., Quiles, M.G., Zhao, L.: Interactive image segmentation using particle competition and cooperation. In: 2015 International Joint Conference on Neural Networks (IJCNN). pp. 1-8 (July 2015)
[7] Breve, F., Quiles, M., Zhao, L.: Interactive image segmentation of non-contiguous classes using particle competition and cooperation. In: Gervasi, O., Murgante, B., Misra, S., Gavrilova, M.L., Rocha, A.M.A.C., Torre, C., Taniar, D., Apduhan, B.O. (eds.) Computational Science and Its Applications - ICCSA 2015, Lecture Notes in Computer Science, vol. 9155, pp. 203-216. Springer International Publishing (2015), http://dx.doi.org/10.1007/978-3-319-21404-7_15

PCC for Interactive Image Segmentation

- Nodes have a domination vector
  - Labeled nodes have ownership set to their respective teams (classes).
  - Unlabeled nodes have ownership levels set equally for each team



Ex: [0.00 1.00]
(2 classes, node labeled as class B)

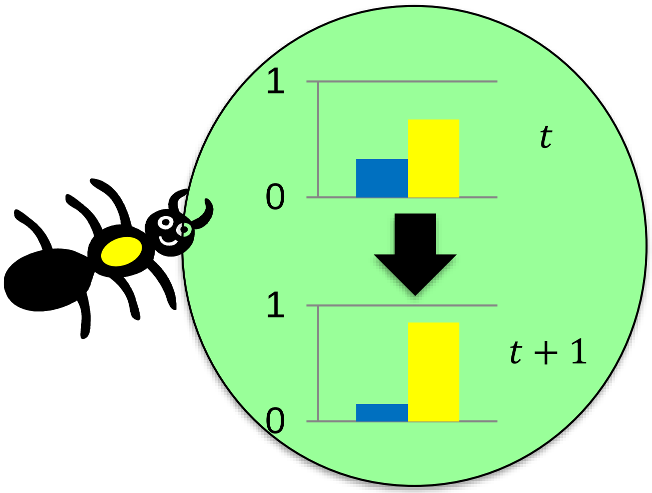


Ex: [0.5 0.5]
(2 classes, unlabeled node)

$$v_i^{\omega_c} = \begin{cases} 1 & \text{if } x_i \text{ is labeled } y(x_i) = c \\ 0 & \text{if } x_i \text{ is labeled } y(x_i) \neq c \\ {}^{1}\!/_{c} & \text{if } x_i \text{ is unlabeled} \end{cases}$$

Node Dynamics

- When a particle selects a neighbor to visit:
  - It **decreases** the domination level of the **other** teams
  - It **increases** the domination level of its **own** team
  - Exception: **labeled** nodes domination levels are **fixed**

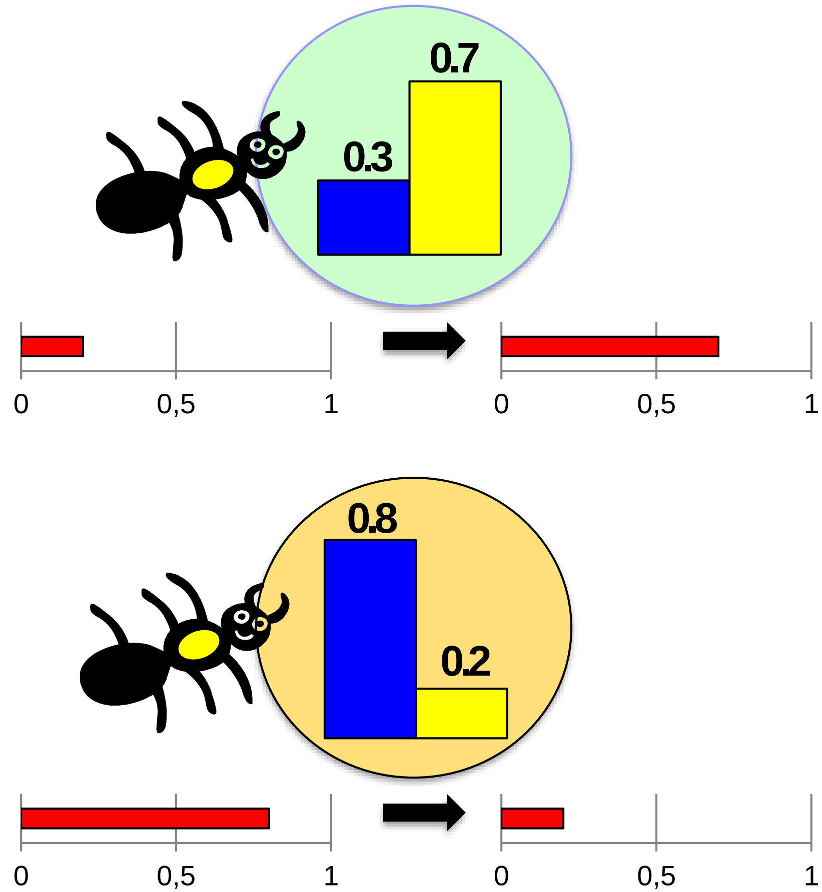


$$v_i^{\omega_c}(t+1) = \begin{cases} \max\left\{0, v_i^{\omega_c}(t) - \dfrac{0.1\,\rho_j^{\omega}(t)}{C-1}\right\} & \text{if } c \neq \rho_j^c \\ v_i^{\omega_c}(t) + \sum_{r \neq c} v_i^{\omega_r}(t) - v_i^{\omega_r}(t+1) & \text{if } c = \rho_j^c \end{cases}$$

Particle Dynamics

- A particle gets:
  - **Strong** when it visits a node being dominated by **its own** team
  - **Weak** when it visits a node being dominated by **another** team

$$\rho_j^{\omega}(t) = v_i^{\omega_c}(t)$$

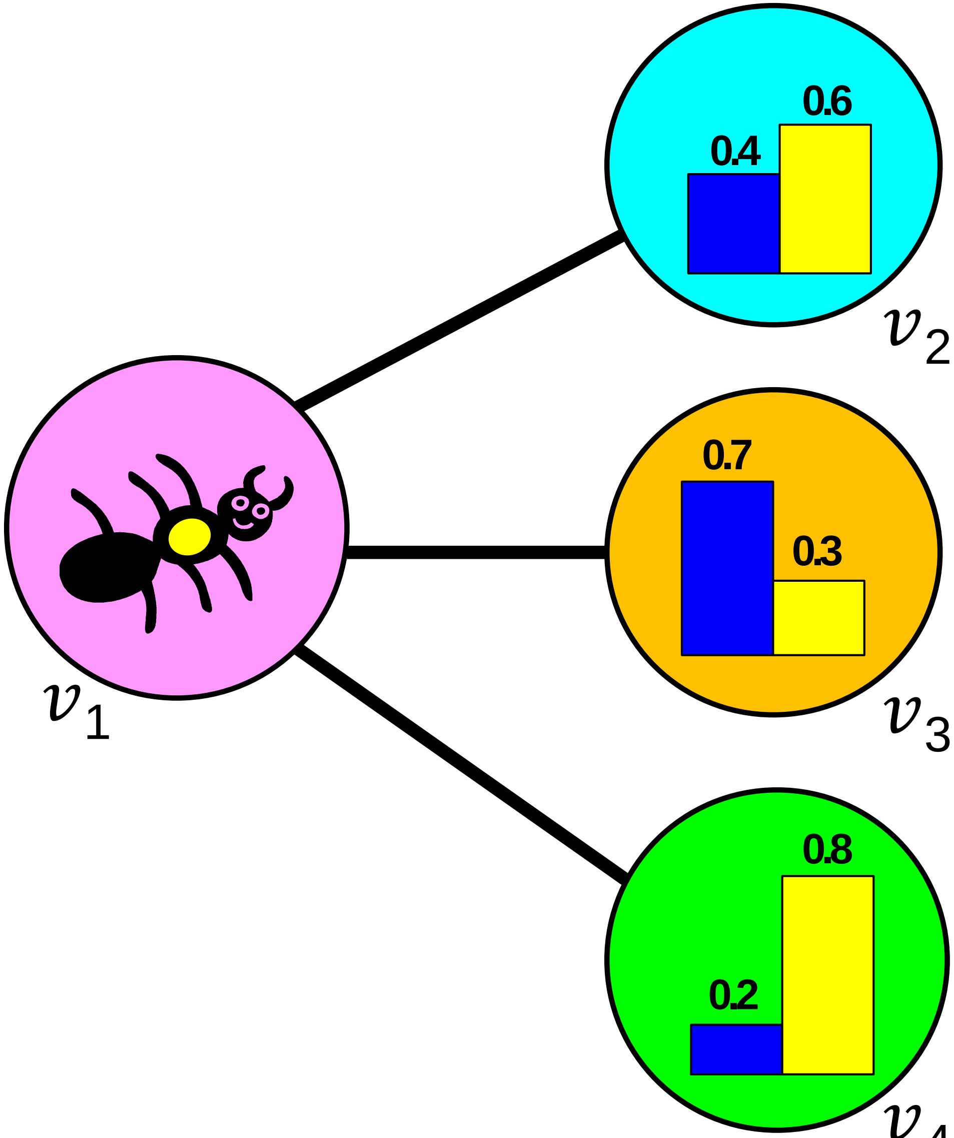


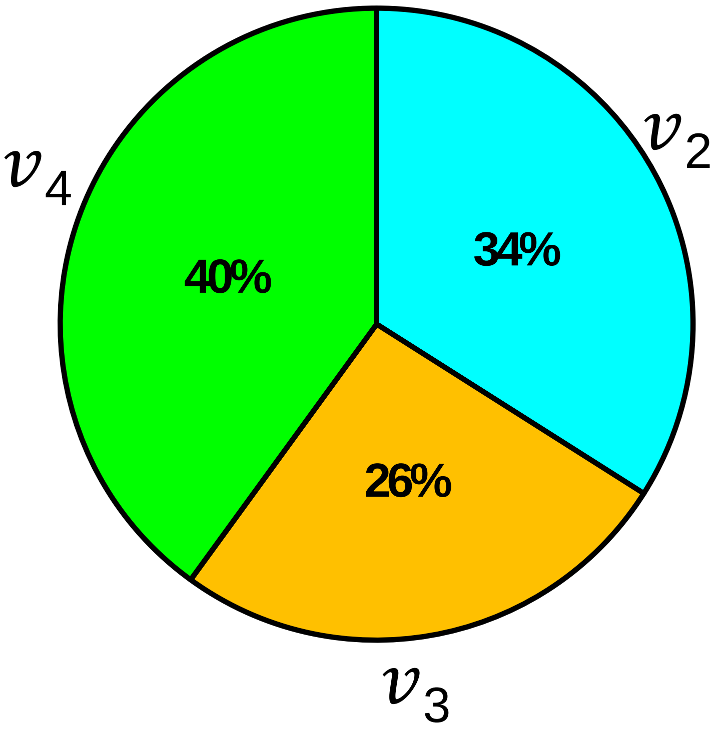
Particles Walk

- Random-greedy rule
  - Each particles randomly chooses a neighbor to visit at each iteration
  - Probabilities of being chosen are higher to neighbors which are:
    - Already dominated by the particle's team.
    - Closer to particle's initial node.

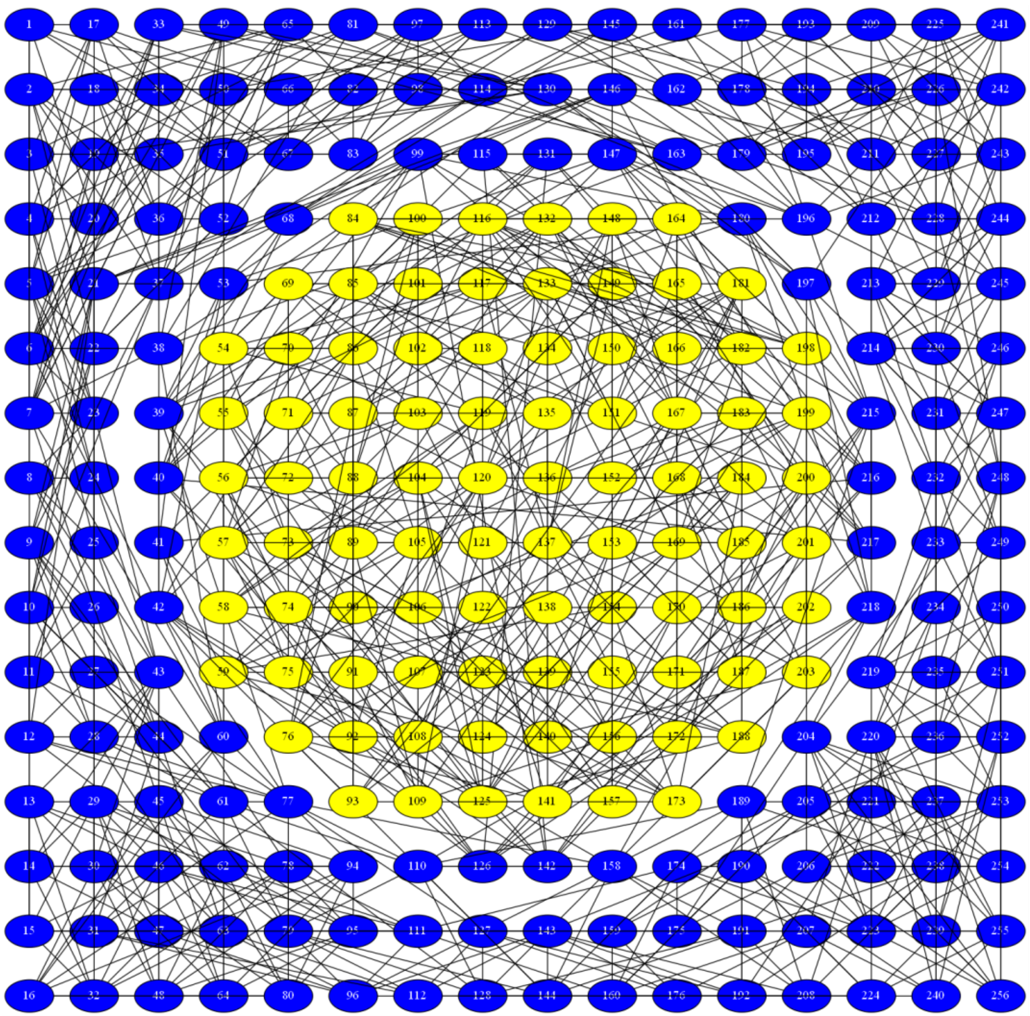
$$p\left(v_i|\rho_j\right) = \frac{W_{qi}}{2\sum_{\mu=1}^{N} W_{q\mu}} + \frac{W_{qi} v_i^{\omega_c}\left(1+\rho_j^{d_i}\right)^{-2}}{2\sum_{\mu=1}^{N} W_{q\mu}\, v_\mu^{\omega_c}\left(1+\rho_j^{d_\mu}\right)^{-2}}$$

Moving Probabilities

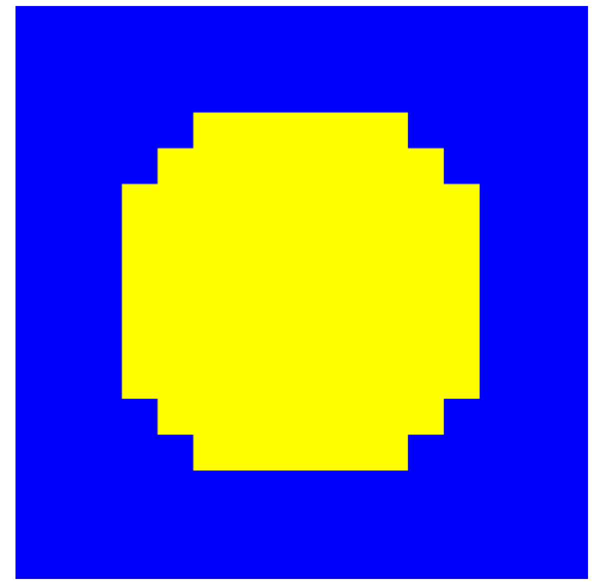




Labeling the unlabeled pixels



(a)



(b)

Proposed Method Segmentation Example: (a) resulting graph after the segmentation process with nodes' colors representing the labels assigned to them; and (b) original image with the pixels colored after the resulting graph, where each color represents different class.

Building Networks for PCC

- 23 weighted features:
  - Pixel position (Row, Column)
  - RGB (red, green, blue) components
  - HSV (hue, saturation, value) components
  - ExR, ExG, ExB components
  - Average of each RGB and HSV components in a 3x3 window
  - Standard deviation of each RGB and HSV components in a 3x3 window

Building Networks for PCC

- Problem:
  - There is **not** a unique set of feature weights which is optimal for all images.
  - Given an image with user marks, how to choose weights that lead to better image segmentation?

Proposed Approach

- Candidates networks are
  - Built with some candidate values for the weight vector λ
  - Evaluated using a proposed network index α
- Therefore, finding a good λ becomes an optimization problem
  - Where the proposed network index α is maximized

Network Index

The network index α is defined as:

$$\alpha = \left(\frac{z_i}{z_t}\right)^{\sigma} \qquad (8)$$

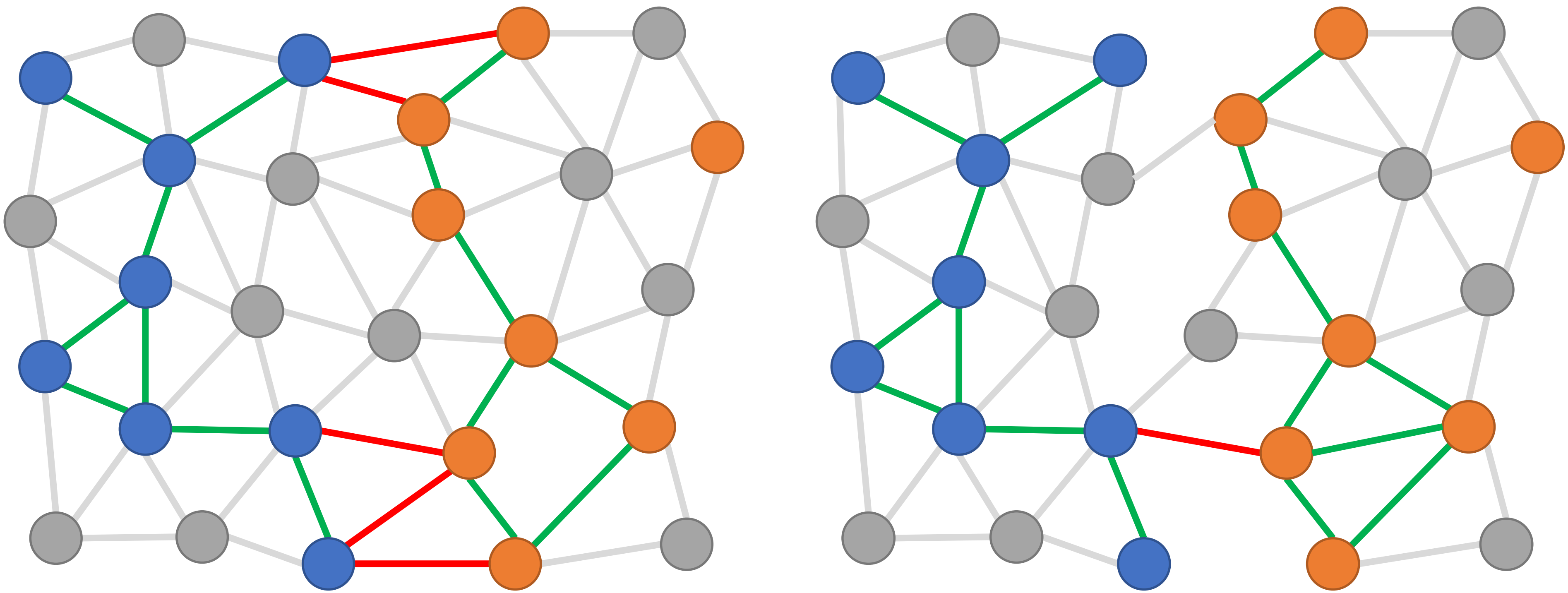
z_i is the amount of edges between pairs of nodes representing the same class

z_t is the total amount of edges between all pairs of labeled nodes, no matter which class they belong

$$\sigma = \frac{\ln(0.5)}{\ln(\Phi)} \qquad (9)$$

Φ is the result of (8) when $\sigma = 1$ and $\lambda = \{1, 1, \ldots, 1\}$.

Network Index: Example

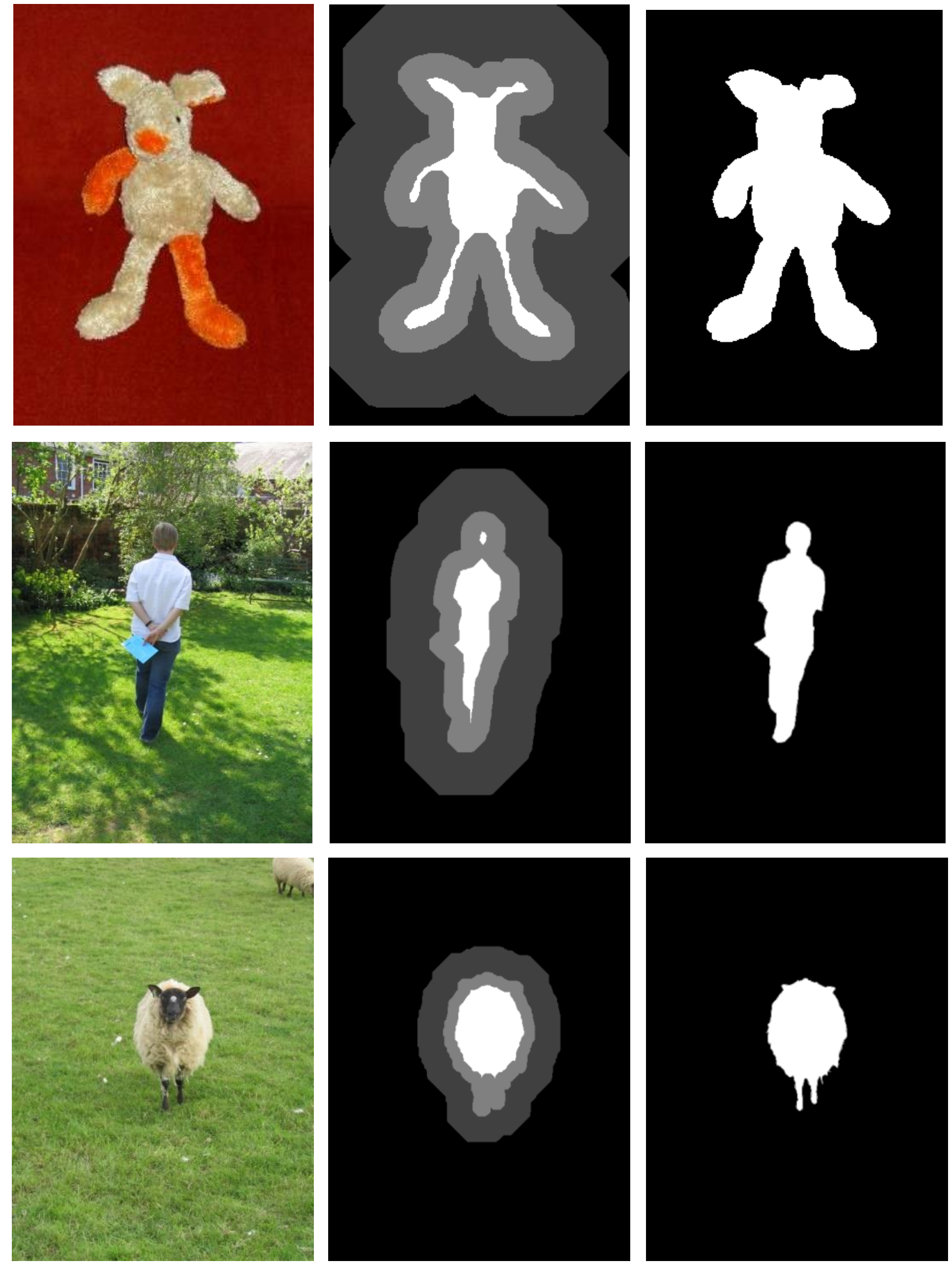


(a) $\alpha = \left(\frac{15}{20}\right)^{\sigma}$ (b) $\alpha = \left(\frac{16}{17}\right)^{\sigma}$

Examples of candidate networks with 27 nodes. Labeled nodes are colored in blue and orange. Unlabeled nodes are colored gray. (a) 15 edges between nodes of the same class are represented in green, while 5 edges between nodes of different classes are represented in red. (b) 16 edges between nodes of the same class are represented in green, while a single edge between nodes of different classes is represented in red.

Computer Simulations

- 3 images were selected from the Microsoft GrabCut dataset



Background, ignored

Labeled background

Unlabeled region, labels will be estimated by the proposed method

Labeled foreground

Computer Simulations

- Baseline
  - 23 features with the same weight $\lambda = \{1, 1, \ldots, 1\}$
  - Different choices of k (the best is taken)
- Optimized feature weight vector λ
  - Optimization using a Genetic Algorithm
    - $k = 100$ (fixed)
    - Fitness Function = Proposed Index (α)
  - Different choices of k (the best is taken) with the optimized λ

(a) Error: 1.89%

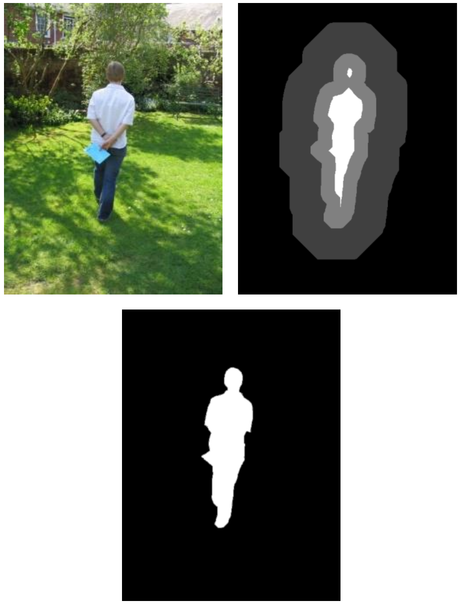
(b) Error: 1.86%

Teddy - Segmentation results achieved by PCC applied to: (a) networks built without feature weighting; (b) networks built with feature weights optimized by the proposed method

(a) Error: 2.81%

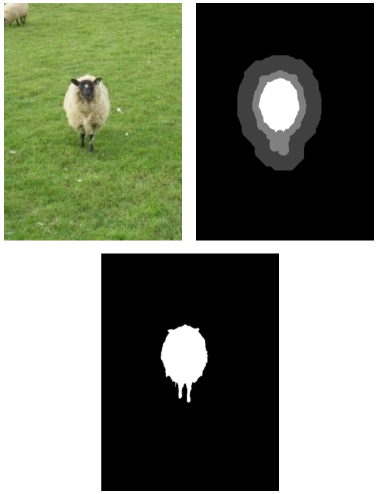
(b) Error: 1.67%

Person7 - Segmentation results achieved by PCC applied to: (a) networks built without feature weighting; (b) networks built with feature weights optimized by the proposed method



(a) Error: 2.90%

(b) Error: 2.04%



Sheep - Segmentation results achieved by PCC applied to: (a) networks built without feature weighting; (b) networks built with feature weights optimized by the proposed method

Results

Segmentation error rates when PCC is applied to networks built without feature weighting (baseline) and to networks built with feature weights optimized by the proposed method

Image / Method	teddy	person7	sheep	Mean
Baseline	1.89%	2.81%	2.90%	2.53%
Proposed Method	1.86%	1.67%	2.04%	1.86%

Optimized k

Image / Method	teddy	person7	sheep
Baseline	48	526	530
Proposed Method	62	210	976

Optimized index α and GA Generations (200 individuals)

Image	teddy	person7	sheep
Optmized Index (α)	1,0000	1,0000	1,0000
GA Generations	1	40	164

Feature weights optimized by the proposed method

Image / Feature	teddy	person7	sheep	Mean
Row	0.5377	0.9293	0.9908	0.8193
Col	1.0000	0.9686	0.9901	0.9862
R	0.0000	0.0550	0.0080	0.0210
G	0.8622	0.1048	0.0700	0.3457
B	0.3188	0.0372	0.0512	0.1357
H	0.0000	0.0476	0.0287	0.0254
S	0.0000	0.0186	0.0562	0.0249
V	0.3426	0.0977	0.0697	0.1700
ExR	1.0000	0.0732	0.0049	0.3594
ExB	1.0000	0.2085	0.0146	0.4077
ExG	0.0000	0.1051	0.1173	0.0741
MR	1.0000	0.0734	0.0237	0.3657
MG	0.7254	0.0674	0.0486	0.2805
MB	0.0000	0.0419	0.0408	0.0276
SDR	0.7147	0.1788	0.0145	0.3027
SDG	0.0000	0.0380	0.0042	0.0141
SDB	0.0000	0.0161	0.0377	0.0180
MH	1.0000	0.0363	0.2545	0.4303
MS	1.0000	0.1754	0.2584	0.4779
MV	1.0000	0.1079	0.0301	0.3794
SDH	0.6715	0.0098	0.1917	0.2910
SDS	0.0000	0.0239	0.1267	0.0502
SDV	0.7172	0.0787	0.0270	0.2743

Conclusions

- A new approach to build networks representing image pixels is proposed
  - Candidate networks are evaluated using the proposed index
  - Feature weights are optimized by the Genetic Algorithm using the proposed index as the fitness function
- The SSL method Particle Competition and Cooperation (PCC) is applied to the optimized network.

Conclusions

- Computer simulations with real-world images show that the proposed method is effectively improving segmentation accuracy, lowering pixel classification error.

- Future work:
  - More images
  - More features
  - Search for some pattern on the images and the corresponding optimized weights
  - Improve the index
  - Eliminate low weight features
    - Feature selection
  - Less labeled pixels
    - “scribbles” instead of “trimaps”

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