Modeling Image Segmentation as Epidemic Spread in an Interdependent Network

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Abstract

We propose formulating the problem of image segmentation as a form of phenomena spread on an interdependent network of superpixels. We define two independent metrics for superpixel similarity and use them to generate two unique, but connected topologies describing the image. We then model image segmentation as the spread of the phenomenon of similarity, using two different propagation models. We then extensively optimize these models against the PASCAL VOC training dataset. Finally we compare our method against a clustering-based baseline algorithm operating on the same superpixelizations.

1 Introduction

Image segmentation is an important and popular topic in computer vision [7, 6, 11]. It is important to note that image segmentation is a distinct but related task to object detection. Notably, image segmentation is not concerned with *what* the objects in an image might be, only *where* they are. Typically this is formulated as assigning a unique label to each pixel in an image, where the label indicates belonging to a particular object. For example, an image containing two cats would be expected to have three labels: one for each cat, and a background label. The current state of the art uses convolutional neural networks.

Interdependent network theory is the branch of network theory devoted to studying the behavior and properties of networks composed of two or more subnetworks, each with different topology or complex interactions. Interdependent network theory is commonly used for analyzing the propagation of phenomena like power failure or social influence through complex networks such as cyber-physical systems and social networks. We propose an interdependent network model of image topology, and explore the use of propagation models to segment the image.

1.1 Related Work

[12] establishes theory for talking about epidemic spread in interdependent graphs. [8, 10] deals more specifically with epidemic spread in complex networks. [2, 5] deals more broadly with the dynamics of interdependent graphs.

[9] use a Markov-Random-Field on precomputed super pixels to perform image segmentation. [7, 6, 11] present a variety of neural network based approached to instance segmentation on natural images.

2 Approach

2.1 Image Network Extraction

To construct our interdependent network model of image topology, first we apply an established superpixelization algorithm (specifically SLIC0) to the image, clustering nearby pixels together into contiguous regions.

Because superpixelization groups similar pixels together, we can approximate the topology of the underlying image using the superpixel network, greatly simplifying future operations.

2.1.1 Alpha superpixel similarity metric

We then define two independent metrics for the similarity of a pair of superpixels. They are ultimately used to generate the topologies of the respective layers of the interdependent network model, so their mutual independence ensures the dissimilar topology of the network layers.

The first metric (the alpha metric) measures the difference in average value (or "brightness") between a pair of superpixels. Initially, each pixel in the image is represented as an RGB color vector x. The alpha metric first computes the euclidean norm of each pixel's vector, and normalizes the result to the range $[0, 1]$. The result is a measure of the pixel's brightness which is independent of its hue or saturation:

$$\alpha_p(\underline{\mathrm{x}}) = \frac{\underline{\mathrm{x}} \cdot \underline{\mathrm{x}}}{\sqrt{3}} = \frac{1}{\sqrt{3}}(\underline{\mathrm{x}}_r^2 + \underline{\mathrm{x}}_g^2 + \underline{\mathrm{x}}_b^2)$$

For a pair of superpixels X and Y, we then define the alpha metric to be the normalized reciprocal of the absolute value of the difference between the average values of the pixels in each:

$$\alpha(X,\, Y) = \frac{2}{1 + |\bar{X}_\alpha - \bar{Y}_\alpha|} - 1$$

$$\bar{X}_\alpha = \sum_{\underline{\mathrm{x}}\,\in\,X} \alpha_p(\underline{\mathrm{x}}),\;\; \bar{Y}_\alpha = \sum_{\underline{\mathrm{y}}\,\in\,Y} \alpha_p(\underline{\mathrm{y}})$$

The result is a real value in the range $[0, 1]$, with lower values representing less similar superpixels.

2.1.2 Beta superpixel similarity metric

The second (or "beta") superpixel similarity metric instead rejects value information entirely, and measures the similarity in saturation and hue between two superpixels. First, it subtracts the vector $[0.5, 0.5, 0.5]$ from the each pixel's color vector, and then divides it by it's own magnitude:

$$\beta_p(\underline{\mathrm{x}}) = \frac{\underline{\mathrm{x}} - [0.5, 0.5, 0.5]}{|\underline{\mathrm{x}} - [0.5, 0.5, 0.5]|}$$

This effectively transforms the color space from the cube between $[0, 0, 0] -> [1, 1, 1]$, to the hollow sphere with radius 1 and centered at the origin. Points on the surface of the sphere represent unique saturation/value combinations. We then average and renormalize these vectors for each superpixel, and take the dot product between them. Because their magnitudes are unit, the dot product effectively measures the cosine of the average angle between the two superpixels in saturation/value space. We finally normalize to the range $[0, 1]$:

$$\beta(X,\, Y) = \frac{1}{2}[1 + \bar{X}_\beta \cdot \bar{Y}_\beta]$$

$$\bar{X}_\beta = \sum_{\underline{\mathrm{x}}\,\in\,X} \beta_p(\underline{\mathrm{x}}),\;\; \bar{Y}_\beta = \sum_{\underline{\mathrm{y}}\,\in\,Y} \beta_p(\underline{\mathrm{y}})$$

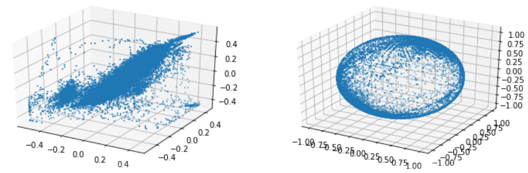


Figure 1: The color space before (left) and after (right) transformation to the sphere

2.1.3 Constructing the network

Next, for each layer we construct the adjacency network over the set of superpixels, and assign weights to its edges based on the above metrics. The result is an α layer and a β layer, which share the same structure, but have independent weightings.

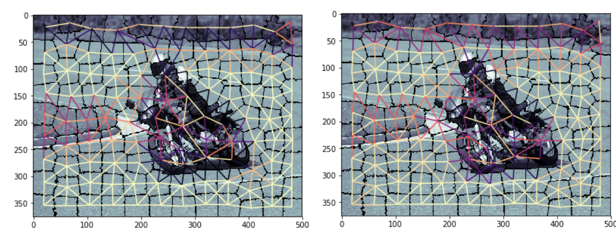


Figure 2: The two layers (α left, β right) of our network model for a sample image

The two layers are then connected one-to-one to form a single network model.

2.2 Propagation

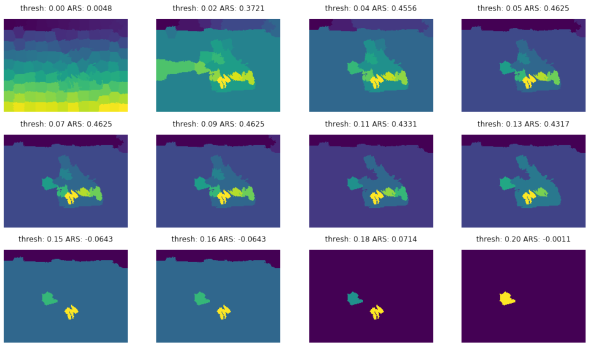
Finally, we are able to perform propagation. We used two models: a markov random-walk model, and a weighted SI-model.

2.3 Baseline

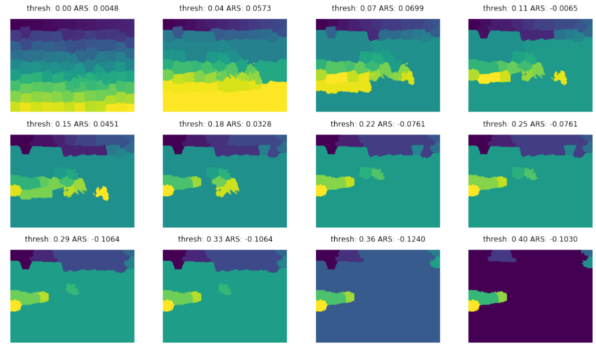
A naive baseline method has been developed for us to compare our actual method against. It is based on using DBSCAN [3] to cluster and merge superpixels produced by SLIC [1].

2.4 Dataset

The dataset upon which we evaluate our method is the PASCAL Visual Object Classification (VOC) dataset [4]. Over the years in which the VOC challenge was run, a couple different variations of the



(a) Sample segmentation using only the alpha scores.



(b) Sample segmentation using only the beta scores.

Figure 3: Each of our proposed similarity metrics provides enough information to perform rudamentary segmentation. To demonstrate this we take a simple thresholding approach, cutting edges below a given threshold, shown above each image. We observe that in this setting, alpha scores seem useful for differentiating between regions in the foreground, and beta scores seem useful for regions in the background. Our intuition is that combining these two metrics will yield superior segmentations.

problem we presented, ranging from whole-image object classification to human pose estimation. In 2012 they introduced a subset of per-pixel image segmentations for $2,913$ of the images in the dataset. In each segmentation, there is a background class, some number of instance classes, and a "don't care" region around each object instance. The image segmentation task is distinct from object classification in that the goal is not to actually classify to which object category each pixel belongs to, but to separate the image into its constituent parts, similar to foreground/background segmentation. We believe that this task presents a unique challenge that can be addressed by our proposed method of propagating information through a interdependent graph defined by pixel/region similarities.

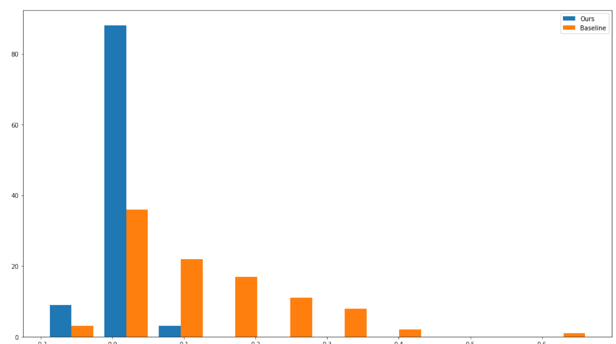


Figure 4: Comparison of Adjusted Rand Score on 100 images from the training set. Having more area to the right of the graph indicates a higher proportion of high quality seqmentations. In this case, this indicates that our method is worse than our defined baseline.

3 Results and Discussion

We evaluate our methods on the Adjusted Rand Score (ARS) from [13]. In Figure 4 we visualize the distribution of ARS for each of our described methods (baseline, Markov-based, and Epidemic-based). In Table 1 we show the average ARS of each method on the PASCAL VOC dataset. Both of the methods proposed in this paper perform worse than the baseline; quantitatively, qualitatively, and in terms of computation time.

Qualitatively, segmentations produced by the Markov-based and Epidemic-based methods leave much to be desired. Figure 5 shows the images and resulting segmentations for the five highest scoring images under each method. The Markov-based segmentations are noisy and typically centered over points of interest in an image. This noise can be attributed to the fact that the likelyhood of arriving in a particular node during a random walk is not uniform when starting in other nodes in a single object.

Each method described is subject to a number of hyperparameters which ultimately dictate the methods performance with regards to ARS. In Figure 6 we show the results of a hyperparameter sweep over

Table 1: Mean Adjusted Rand Score for each method covered in this paper. Higher values indicicate higher quality segmentations.

Method	Mean ARS
Baseline	0.1385439
Markov-based	0.0536634
Epidemic-based	0.0124122

both the Markov-based and Epidemic-based methods. They share the a parameter controling the threshold at which each proposed segmentation is binarized at. Interestingly, each method demonstrates its own sensitiveity to the parameter. Specificly, the Epidemic model is relatively insensitive to it. We attribute this to a quirk of the Epidemic-based method, proposal segmentations that begin in areas with low neighboring similarity will not spread far. Due to the way that we combine proposed segmentations, this produces many smaller, less informative segments. Effectively we are amplifying noise in the signal. In Figure 7 we demonstrate what happens when we use a simple heuristic to select the best proposals.

4 Conclusion

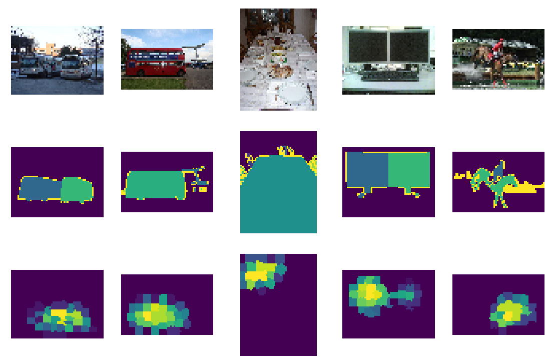
In this document we presented a method for performing instance segmentation on photographs by modeling instance membership as an information spread or epidemic model in an interdependent graph. We introduced two simple similarity metrics which are used as the basis for tranmitting instance membership between neighboring pixels. Finally we compare our method to a rudamentary baseline.

4.1 Future Work

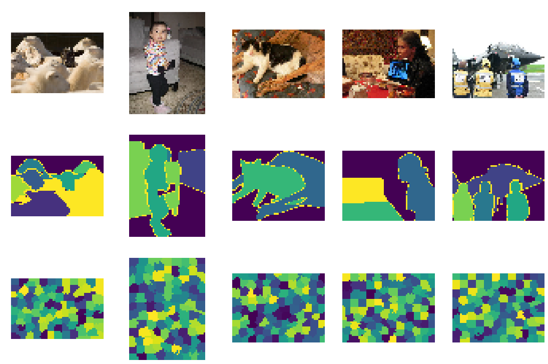
These methods did not perform better than the proposed baseline. Some possible directions for future work include the following:

- Improving the method by which we combine candidate segmentations.
- Incorporating additional similarity metrics, and additional layers to the interdependent graph.
- Explore the effect of using other superpixel segmentation strategies.

(a) Baseline



(b) Markov random walk based



(c) Epidemic based

Figure 5: Sample results from each of our proposed methods.

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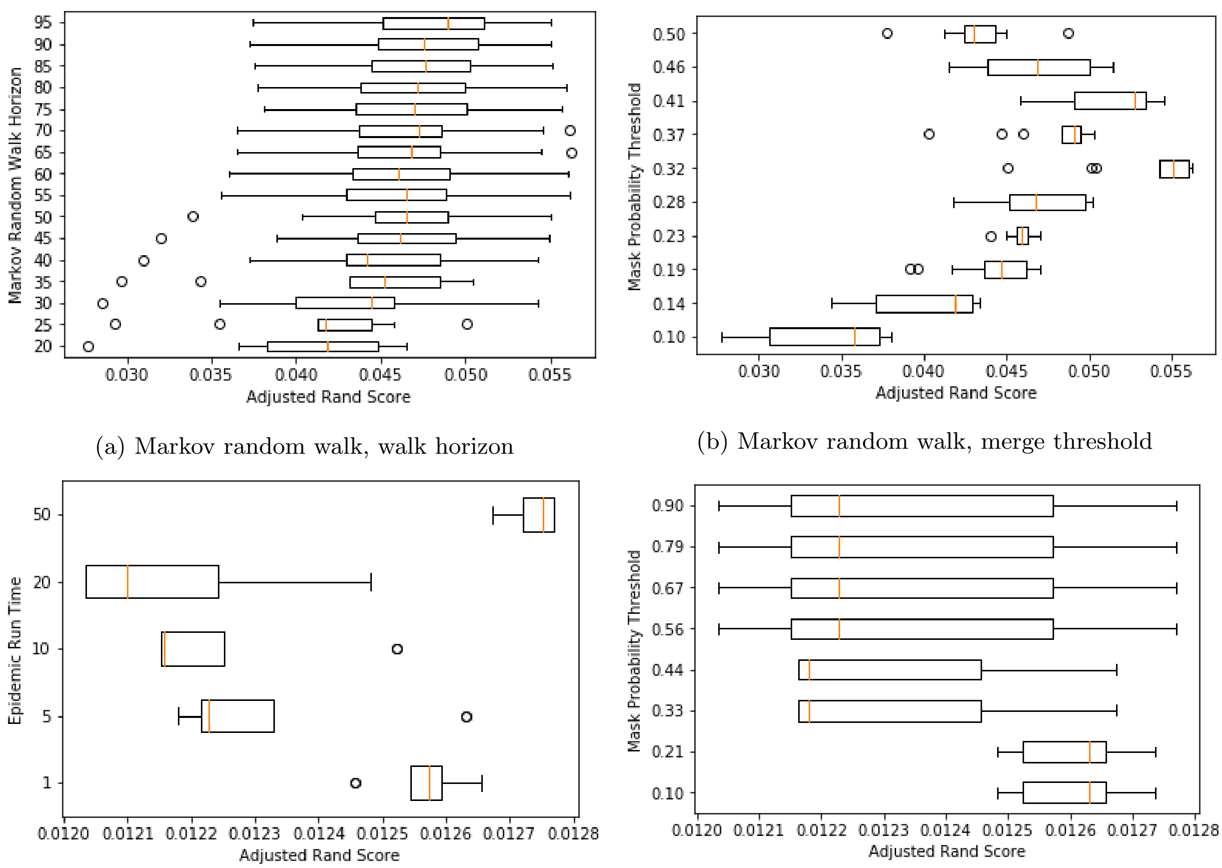

(a) Markov random walk, walk horizon

(b) Markov random walk, merge threshold

(c) Epidemic, simulation runtime

(d) Epidemic, merge threshold

Figure 6: Analysis of performance under different hyperparameters for each of our proposed methods. (a) and (b) show that threshold is the most important parameter for the Markov-based method. (c) and (d) show that simulation run time is the most important parameter for the Epidemic-based method.

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Figure 7: Binaried segmentations proposed by the epidemic-based method, sorted by our simple heuristic.

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