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Image Segmentation Using Fuzzy Spatial-Taxon Cut: Comparison of Two Different Stage One Perception Based Input Models of Color (Bayesian Classifier and Fuzzy Constraint)

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Abstract

Computer vision is typically thought of as an open-universe problem because every possible outcome is unknown. Image segmentation via fuzzy-spatial-taxon-cut reduces image segmentation to a closed-universe problem by assuming a standardized natural-scene-taxonomy, comprised of spatial-taxons. People describe spatial-taxons as thing-like, a group of things or the foreground[2]. They share properties, border ownership in particular, with proto-objects described in biological vision [17]. By defining spatial-taxons in a hierarchy, we operationalize the image segmentation problem into a series of iterative two-class inferences. As described in earlier publications, this method out performs other segmentation methods for well-defined image classes and forms the basis of some commercial image-processing systems. This paper explores how the methodology used to provide the inputs to the low-level color-parsing stage affects overall image segmentation performance by comparing the effects of two methods: fuzzy constraint and Bayes classifier. We discuss how these methods alter the performance the of two-class fuzzy inference system discussed in earlier work.

Introduction

Computer vision systems can, like people, parse an image into several different meaningful pixel regions, depending on viewer context. This creates uncertainty as to how to decide which pixels to include or not include within a region. In this paper we use two different mathematical techniques for decision-making under uncertainty: Fuzzy inference, and Bayesian inference. Fuzzy techniques describe it as ambiguity in event definition, which they rank as degrees of partial-truth, given prior evidence. Bayesian techniques describe it as the relative belief about the occurrence of an event, given prior evidence.

Examine the picture taken from the Microsoft mscoco data base in Figure 1. Imagine a viewer who wants to grab the apple. The mscoco annotation parses the image into mutually exclusive regions: the apple, the reflection of the apple and the bottles. But isn't the reflection of the apple also an apple? To compute the familiar ROC (receiver operating characteristic) we count the hits, false alarms, correct rejections and false rejections. How should we count the pixels within the apple reflection? What about a parsing (or segmentation) that includes all the objects in the foreground? Intuitively, we know it's partially true to include the apples reflection as a partially correct hit. Likewise, we know to attend to (and include within our scene segmentation) the foreground objects if we need to reach across the bottles to grab the apple. But, one would not want to reach for the reflection of the

Figure 1. *(Picture from Microsoft image segmentation and labeling database: http://mscoco.org/explore/?id=481165.*

Fuzzy Set Theory	**Boolean Logic**
$A \cap \neg A = \textit{semantic uncertainty}$	$A \cap \neg A = \oslash$
membership in set A. denoted μ_A can take partial of truth within the interval [0,1] where zero is false, a number between zero and one is the degree of truth and 1 is true.	membership in set A can take the truth values of zero, which means false or one which means true.

Figure 2. *Table 1: Fuzzy set theory and classical (Boolean) set theory.*

apples (hence a partial truth value for the apple reflection, not a 100 percent truth value (Boolean)). In fuzzy set theory, the intersection between a set and its complement equals the semantic uncertainty due to ambiguity (fuzziness) in the definition of events included in the set. In probability theory Kolmogoro's Law Of The Excluded Middle requires that a set and its complement equal an empty set. Both set theory and probability theory handle different types of uncertainty. Used together, they provide a powerful toolbox.

In his paper Computer Vision Needs a Core and Foundation[34], Alan Yuille discusses how the phenomenal growth in computer vision motivated him to co-organize the 2011 Frontiers of Computer Vision Workshop at MIT [1]. He quoted a student who didn't know how to get up to speed simply because

[1] http://www.frontiersincomputervision.com

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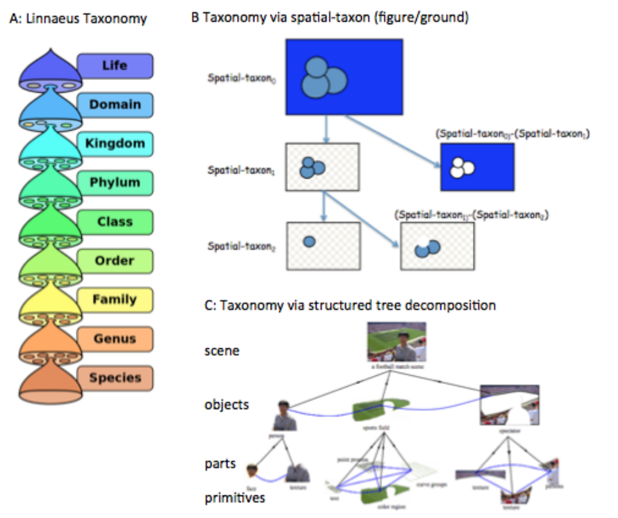

Figure 3. *Three examples that used discrete classification (taxometrics) scale instead of continuous scale to tease apart theoretical structure. A. Linnaeous taxonomy (image taken from Martz, J. (2011). B. Spatial-taxon taxonomy (Barghout 2014). C. Structured tree decomposition taxonomy (Chen, Yuille and Zhu 2005)*

the flood of computer vision papers stymied him from selecting a few must read papers. He stressed the need to find unifying theories that underpin the success (and failures) of these techniques and illustrated problems caused by the heavy use of a limited set of databases. In this spirit, I want to encourage crossover between the Fuzzy and Bayesian inference computer vision techniques and thus wrote this as primarily a 'methods' paper. This desire motivated my upcoming book: Essential Computer Vision: Fuzzy and Bayesian techniques (O'Reilly media). I invite interested readers to contact me for early chapter copies (summer 2016) and welcome suggestions on how to improve the book.

Spatial-taxons

In the late 1700s the naturalist Carl Linnaeus, operationalized the problem of organizing specimens of life into a nested class inference problem by introducing the familiar taxonomy shown in Figure 2A.[24] I borrow his idea and organize pixels into the spatial-taxon taxonomy shown in figure 2B. [1] [3] Other segmentation systems use different taxonomies, such as the example in Figure 2C.[31] Unlike the tree decomposition taxonomy in 2C, the spatial-taxon taxonomy is defined recursively: each child taxon uses the same classification criteria as its parent [2]. I named the classes spatial-taxons because they are specified via their image-topic position (hence the term spatial) and are discrete categories (hence the term 'taxon '). They are not defined on a continuous scale, but occur in discrete regions[3]. Unlike biological vision, which extends throughout space, cameras restrict an image within a frame aperture. Thus I specify my formal definition of spatial-taxons on image-topic map.

Definition: Spatial-taxon

Let X be the universe of discourse consisting of all pixels within the rectangular (or square) pixel array of an image, such that $X_{1,1}$ is located at the upper left corner, and pixel $X_{I,J}$ at the lower left corner. Let ST_0 be a non-empty set that contains all pixels in the universe of discourse (the image-topic map). ST_0 has two mutually exclusive children ST_1 and ST_0-ST_1 such that $ST_1 \cap (ST_0\text{-}ST_1) = \emptyset$ and $ST_1 \cup (ST_0\text{-}ST_1) = ST_0$ (the parent). We have now defined the abstraction level 0 (the whole image) and level 1 (the foreground). The most abstract information granule is the whole image, and the second most abstract level contains two mutually exclusive subsets.

Lets next define the set ST_1 as having two children subsets: ST_2, (ST_1 - ST_2). As with the perception of figure and ground, these children are mutually exclusive, such that that $ST_2 \cap (ST_1\text{-}ST_2) = \emptyset$ and $ST_2 \cup (ST_1\text{-}ST_2) = ST_1$ (the foreground). This is the third most abstract level in the nested spatial-taxon hierarchy.

In this work, I use the segmentation engine described in the chapter in Granular Computing and Decision Making: Interactive and Iterative Approaches (Barghout 2015), however we exchange the color-parsing inputs for those derived from a Bayesian classifier. We compare the spatial-taxons produced by the previous work with those produced with the Bayesian classifier inputs using the same high-level inference system.

Inference systems

For simplicity, we describe both Bayesian and Fuzzy inference systems in three phases. Bayesian inference starts with a prior model of the known (phase one), extracts a likelihood of the prior variable after collecting observations (phase two) and infers the posterior via Bayes law (phase three). Fuzzy inference starts with a model of partial-truth membership functions of what is known (phase one), invokes fuzzy logic - similar to predicate logic (phase two) and returns a defuzzified (Boolean) answer (phase three).

Figure 4 shows how we obtain phase one for Bayesian (left) and Fuzzy (right) prior.

In the Bayesian case, I used a highly modified version of the Bayesian hierarchical model introduced by Fei-Fei & Perona (2005) [13] called patch-based Dirichlet latent allocation. Dirichet latent allocation was introduced [8] by Blei and colleagues as an unsurpervised machine learning technique for modelling topics within a large text document corpora. The techniques exploits three facts: (1) documents discuss several topics; (2) word frequency conditionally depends on topic discussed; and (3) the Dirichlet distribution is conjoint across Bayes law [4]. The method first learns the latent structure of topics (which co-occur with documents (top level of the Bayesian hierarchy), and then it learns the latent structure of words that co-occur within topics (second level of Bayesian hierarchy). This two step hiearchy results in 'bags of words' representations that can be used to generate new topic and document models. When confronted with a yet to be analyzed document, this system generates a model of the new document from the learned latent structures 'topic word bags

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[2]In practice, we halt recursion when the perceptual input variables (also called cognitively relevant variables [5] are not isomorphic a human phenomenological counterpart.

[3]To distinguish the difference between continuous and discrete scales, consider an analogy from visual attention. The spot light theory of attention [32] extends along continuous dimensions in space. Object based attention snaps (in discrete jumps) to objects or object groups.

[4]In otherwords, if the prior probability is a multinomial Dirichlet, it's posterior is also a multinomial Dirichelt.

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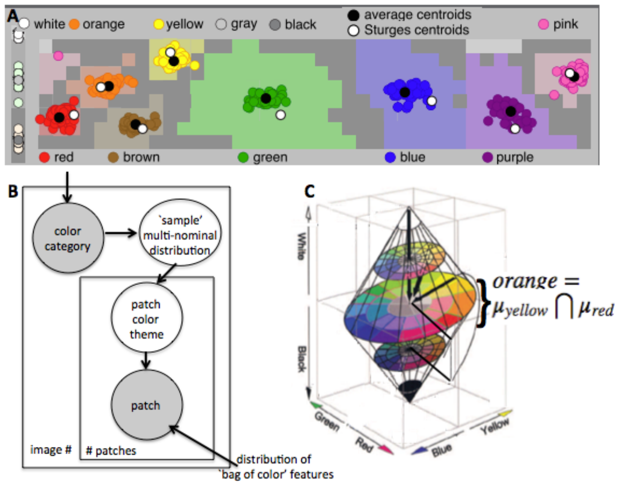

Figure 4. *Instead of learning latent color visual words from a training corpora (as in Fei-Fei & Perona 2005), I extracted the distributions for 12 color words from English speaker color survey - replacing the unsupervised learning part of the Bayesian hierarchy with the labeled color distributions. A. The centroid mapped on the world-color-survey Muncel chart (taken from Linsey and Brown 2014). B. Bayesian model modified from Fei-Fei & Perona 2005. Within the large box (image) are observed (in gray) color categories distributed over multinomial sample distrbution (in white). Generative model comprised of patches (small box) with color themes (co-occurences of color features) used to classify color category via a 'bag of color ' patch. (Note: a patch is analogous to a 'code word 'in the topic modeling liturature, a texton (or convolution filter) in computer vision or a 'shape epitome 'image labeling (Chen2013)) C. Fuzzy membership functions derived from color spindle. The example of derived color of orange is shown.*

'. The topics of the new document are infered via traditional three phase Bayesian inference described earlier.

I thank Anthony DiFranco, who uses latent Dirichelet allocation (LDA) for topic modeling of wikipedia entries, for suggesting LDA as a Bayesian comparison model. Anthony adapted his topic modeling code into a patch-based Bayesian model in our earlier collaboration.

As Brainard (2009) states: "Bayesian analysis provides a framework for generating models that may be applied to specific perceptual phenomena. The task of the modeler is to express the content of interest as a likelihood and prior, and then to link the resulting estimate of the scene parameters to perception. The framework is useful to the extent that it consistently generates models that describe, predict, and clarify empirical data. "[6] The specific perceptual phenomena required by the fuzzy inference system are image-topic estimates of pixel color category for the input image given the prior extracted from the color naming survey and the likelihood sampled from the 'bag of color ' patches.

In the fuzzy case, the input domain, referred to as the universe of discourse in fuzzy set theory and the event space in probability theory, was converted from red green blue (RGB) coordinates to hue, saturation and intensity (HSI). The numerical values approximate 12 non-mutually exclusive volumes cut from the color spindle shown in the three dimensional volume color spindle (shown in 4b). The spindle varies along three dimensions: hue (H: angle around the color circle), saturation (S: distance from

$$I = \tfrac{1}{3}(R+B+G)$$
$$S = 1 - \tfrac{3}{R+G+B} min(R,G,B)$$

when hue is between 0 and 180

$$H = \left[\frac{\frac{1}{2}[(R-G)+(R-B)]}{\left((R-G)^2+(R-B)^2(G-B)\right)^{\frac{1}{2}}} \right]$$

and when hue is between 180 and 360

$$H = 360 - \left[\frac{\frac{1}{2}[(R-G)+(R-B)]}{\left((R-G)^2+(R-B)^2(G-B)\right)^{\frac{1}{2}}} \right]$$

where hue is normalized between zero and 1 (H=H/360)

Figure 5. *Formulas for converting from RGB to hue, saturation and intensity (HSI).*

Human color phenomenology (percept), semantic variable (category set), modified from Kay & McDaniel 1978.

Human Color Percept	Semantic variable	Characteristic membership via identity relation
Black	μ_{black}	$K(Saturation_{black_o}, \sigma_{black_o}) * K(Intensity_{black_o}, \sigma_{black_o})$
White	$\mu_{white} =$	$K(Saturation_{white_o}, \sigma_{white_o}) * K(Intensity_{white_o}, \sigma_{white_o})$
Red	$\mu_{red} =$	$K(Hue_{red_o}, \sigma_{red_o}) * K(Saturation_{red_o}, \sigma_{red_o}) * K(Intensity_{red_o}, \sigma_{red_o})$
Yellow	μ_{yellow}	$K(Hue_{yellow_o}, \sigma_{yellow_o}) * K(Saturation_{yellow_o}, \sigma_{yellow_o}) * K(Intensity_{yellow_o}, \sigma_{yellow_o})$
Green	$\mu_{green} =$	$K(Hue_{green_o}, \sigma_{green_o}) * K(Saturation_{green_o}, \sigma_{green_o}) * K(Intensity_{green_o}, \sigma_{green_o})$
Blue	$\mu_{blue} =$	$K(Hue_{blue_o}, \sigma_{blue_o}) * K(Saturation_{blue_o}, \sigma_{blue_o}) * K(Intensity_{blue_o}, \sigma_{blue_o})$

Figure 6. *Fuzzy membership functions for each primary color. Fuzzy membship of derived colors are the intersections of primary colors.*

midline) and brightness (I: height along the midline). The equations below convert pixel rgb values into HSI values. The torus ringing the middle of the spindle contains the most vibrant colors. Monochromatic colors live on the middle axis and de-saturated pastels live between the center and vibrant colored surface.

For each color, the fuzzy membership (known model) is the intersection of three kernels: hue, saturation and brightness. Red, green, blue and yellow are centered at 0, 1/3 (360/120), 1/3 (360/240, 1/6 (360/60) with standard deviation of 1/6, 1/6, 1/6, and 1/9 respectively. The saturation kernels are all centered at one with a standard deviation of 1/2. Intensity for red, green, blue and yellow are centered at 1/2, 1/2/ 2/6 and 4/6 with standard deviations of 1/3. Though we picked our initial kernels according to world color survey, we use long tail distributions (since is possible for a pixel that might appear dark blue in isolation to appear green when context indicates its part of a green leaf (like the ambiguously colored dress)). In practice we began with these kernels then modified the shapes slightly via method of adjustment to match the color appearance of a single user. The table below shows how the fuzzy membership functions are related to these three kernel. Due to limited space, we left out the derived colors. However, figure 4b shows how to carve the membership of orange from the fuzzy intersection of yellow and red. Also note we parse a 12th color, light-blue, the intersection of white and blue.

Now that we have fuzzy representations, we perform fuzzy

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inference via the familiar logical steps:

Knowledge : memberships & rules

Facts : partial truths

Conclusion : fuzzy implication

Once the 12 non-mutually exclusive fuzzy color memberships for the image are known, fuzzy implication (Mamdani) aggregates the predicates. For example the fuzzy membership of orange is red and yellow. So $\mu_{orange} = \int_{universe\ of\ discourse} \mu_{red} \cap \mu_{yellow} / cardinality(universe\ of\ discourse)$

Method

What is a well-defined image class?

The spatial-taxon view of scene perception assumes that humans parse scenes not between regions of similar features that vary continuously, but instead via discrete image-topic jumps biased toward taxometric scene configurations.[28] [4] Segmenting images into meaningful regions for ground truth databases is prerequisite testing computer segmentation algorithms. Yet region relevancy depends less on segmenting specific objects then on the abstraction level within the spatial-taxon taxonomy. This is particularly true for visual components necessary for the specific tasks.

I addressed this problem by adding two requirements to ground-truth regions used in this testing. First I required 80% of humans to agree on the center of the subject of interest, which indicates appropriate level of abstraction (Barghout 2009). Second (and this is specific to my inference system) I test via a two-alternative-force-choice procedure that the scene decomposition rules used by the fuzzy-interence-system correlate with human detection of these rules. This is a tricky procedure and not necessary for unsupervised learning techniques.

Processing Pipeline

The inference system [2] applies four scene composition rules: (1) spatial-taxon distinguishes itself from the background via strongly weighted uniformly connected color and somewhat similar background colors adjacent to aperture frame; (2) spatial-taxon contains high spatial-frequency structure and background adjacent to aperture frame shares colors and contiguous low spatial frequency structure (in other words a blurry connected region); (3) the system knows nothing about the characteristics of the spatial-taxon, but it knows the background is low spatial frequency (blurry), of similar color and adjacent to the aperture and (4) the spatial-taxon shares similar contiguous colors and the background contains different but similar contiguous colors. In addition any region of strong bi-lateral symmetry is weighted toward being a spatial-taxon. The fuzzy inference system and decision making system used to adjust rule weights are detailed in Barghout 2014 & 2015.

The prior knowledge of the four composition rules are stored in the database illustrated in figure 7. Various combinations of inference rules are sent to the decision making process (figure 7), which choses the combination of hypothetical spatial-taxons that maximizes utility and minimizes attentional resourses. See Barghout 2015 for details on the decision making engine. In the final stage the optimal hypothetical spatial-taxon combination

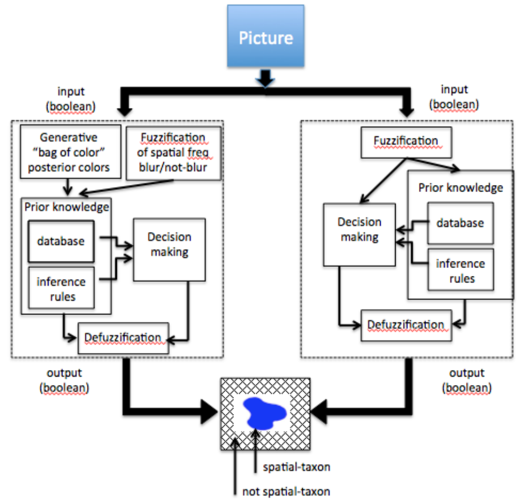

Figure 7. Processing pipeline. The left processing stream uses the stored Bayesian 'bag of colors 'to produce up to 12 posterior color parsing distributions for the input image. The Bayesian model is augmented by a fuzzy parsing of blurry and not-blurry regions (see Barghout 2014 for more details). The rest of the pipeline is identical to the fuzzy inferece system shown on the right. Both systems produce mutually exclusive spatial-taxon and background regions.

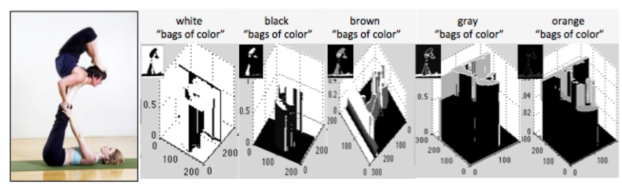

Figure 8. Internal 'bag of color ' structure for the top 5 probable colors. From left to right are the original photo, the white distribution, black distribution, brown distribution, gray distribution and orange distrution for each pixel on the image-topic. I rotated the axis to improve view. In the top-down left of each mesh is a top down view. Probability decreases from white (highest probability)

along with the optimal inference rule weights is defuzzied into a Boolean output as shown in figure 7.

The fuzzy inference system used in this paper applies the four composition rules just described. The Bayesian computer vision liturature refers to this type of inference as geometric bag-of-features or spatial bag-of-features [16].

Results

Figures 8 and 9 show five of the 12 possible Bayesian and Fuzzy color parsings for an example image.

In the Bayesian case, I sorted from left to right the most influential internal 'bag of color' structures. The white 'bag of color' has the highest posterior and covers the largest image-topic area. It's difficult to see this from the mesh plot, though I rotated the axes to improve the view, but it's easy to see from the top down view in the upper left corner. The black 'bag of color' does a good job of parsing the black clothing and hair. Unfortunately, the brown and gray posteriors and all the other 'bag of colors'

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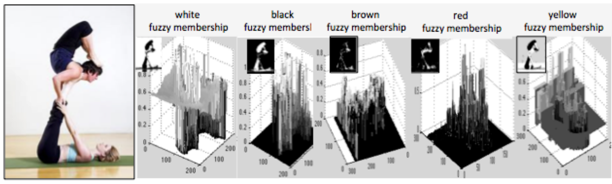

Figure 9. *From left to right: origianl image, white fuzzy membershp, black fuzzy membershp, brown fuzzy membershp, red fuzzy membershp and yellow fuzzy membership. Axes rotated to match those of Bayesian color parsing in figure 9.*

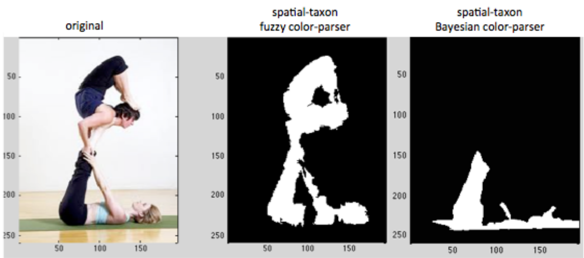

Figure 10. *Spatial-taxon inferred by the fuzzy inference system with the fuzzy color parsings (middle) and Bayesian 'bag of colors ' for the original image on left.*

save orange posteriors miss classify the skin as white - creating two disjoint regions. As per the decision making algorithm described in Barghout 2014a, 2015, the fuzzy inference system decided the highest utility was obtained by grouping the co-occuring color parsings of the bottom woman as shown in 10c.

In the Fuzzy case, figure 10 shows fuzzy membership white, black and brown in the same view as the Bayesian case. As in the Bayesian bag of white region, the high luminance of the wall and floor returned high degrees of paritial truth for the same image-topic areas - as can be seen in the top down view in the upper left. Unlike the Bayesian case, the fuzzy membership provided richer spatial variation. The rich spatial complexity co-occures with brown, red and yellow. Thus the hypothetical spatial-taxons in the fuzzy inference system could build a uniformly connected region which as per Barghout (2014a, 2015) had high utility resulting in the spatial-taxon segmentation in figure 11.

Discussion

This paper represents a first start in systematically combining the tools of fuzzy and Bayesian inference, but much more needs to be done.

The Bayesian model requires a discrete set of features (multinomial variables), in our case 12 color categories. To generate the patch kernal, $patch_n \sim p(patch_n \mid (patchcolortheme)_n, featuredistribution)$ which tends to over segment color parsings.

In the example shown in the results section, the Bayesian method doesn't provide enough overlap for the fuzzy inference system to group the spatial-taxon with any of the four scene composition rules. This was the case for most of the images in the test copora from Barghout 2015. This may be an artifact due to my infering the latent structure from the Muncell color distribution instead of learning it from a large test corpora which may have inferred latent structure that supported the merging of color topics.

Another problem with the Bayesian implementation stems from the lack of lightness constancy anchoring. The Bayesian parser was highly biased toward white, probably because there was no lightness constancy constraints built into the prior model. Again, this may have been learned from the latent structure of a large test copora. Since the fuzzy membership functions, carved from the color spindle, it incorporated a de-facto white anchor due to the distance between white and black intensity being anchored to about 1.5 log units.

Conclusion

In conclusion, image segmentation via fuzzy-spatial-taxon-cut reduces image segmentation to a closed-universe problem by assuming a standardized natural-scene-taxonomy, comprised of spatial-taxons. This inference system provides a frame in which Fuzzy inference and Bayesian inference techniques can be encapsulated and compared. Further work is needed to modify the Bayesian model to reduce the over segmentation problem and introduce lightness constancy constraints.

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Author Biography

A scientist, inventor and serial entrepreneur, Lauren holds a Ph.D. and M.S. in Vision Science from the University of California at Berkeley and a Bachelors degree in Physics from Hampshire College. She is an expert in the use of fuzzy set theory in representing Visual Gestalts and inventor of the Gestalt-based image segmentation and labeling technique that underpins natural vision processing system used commercially in the image background removal and image labeling sector. She is currently a visiting scholar in the Lotfi Zadeh (inventor of fuzzy logic) group at EECS at U.C. Berkeley.