Fusion of Bayesian Visual Classifiers

xiaojin Shi
05/03/2002

Schedule

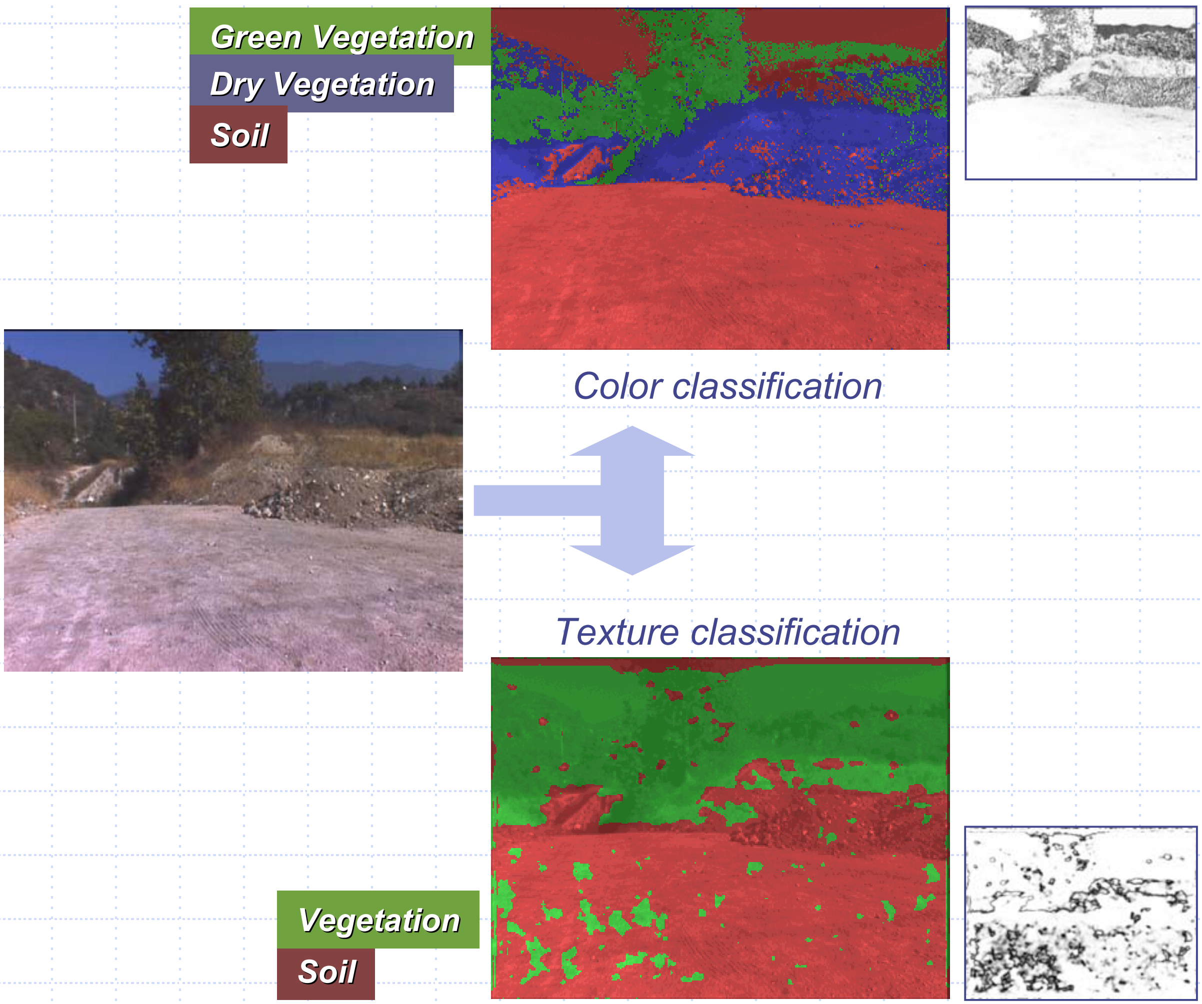
- Background
- Previous work
- What we are doing
- Future work

Background

- The problem we are addressing…
  - ✓ Classifying a scene into a number of known objects
  - ✓ Fusion of classifiers…

Background

- The problem we are addressing…



Background

- Classification of the approaches dealing with the problem
  - ✓ Create a super-feature
  - ✓ Fuse together the results of the classifications

Background

- Bayesian theory:
  - Definition:

    Prior: $p(j)$

    Likelihood: $p(y|j)$

    Posterior: $p(j|y)$
  - Bayesian rule:

$$p(j|y) = \frac{p(j)\,p(y|j)}{p(y)} \propto p(j)\,p(y|j)$$

Where $p(y) = \sum_j p(j)\,p(y|j)$

Previous Work

- Bayesian fusion technique:

$$p(j \mid f_i) = \frac{p(j)\,p(f_i \mid j)}{p(f_i)} \qquad p(f_i) = \sum_{j=1}^{N} p(j)\,p(f_i \mid j)$$

Assume the conditional likelihood are independent, i.e.,

$$p_{12}(f_1, f_2 \mid j) = p_1(f_1 \mid j)\,p_2(f_2 \mid j)$$

We have:

$$p_{12}(j \mid f_1, f_2) = K_{12}(f_1, f_2)\,p_1(j \mid f_1)\,p_2(j \mid f_2)\,p(j)$$

$$K_{12} = \frac{p_1(f_1)\,p_2(f_2)}{p_1(f_1, f_2)}$$

What We Are Doing…

The case of different sets of classes:

- Problem: classifiers relative to different features may be trained on different sets of classes.
- Approach:

  Construct the compound set:

  $$\bar{c} = \bigcup_{i,j} (c_{1i} \bigcap c_{2j})$$

  Classify over the compound set:

What We Are Doing…

- Approach:
  - The likelihood:

    Assign the same conditional likelihood;
  - The prior:

    The sum of the subclass priors within c_{im} is Equal to the prior for c_{im}
  - Decision rule:

    Bayesian fusion.

What We Are Doing…

Outliers:

- The importance of dealing with the problem: Bayesian theory is lack of support for the notion of “ignorance”.

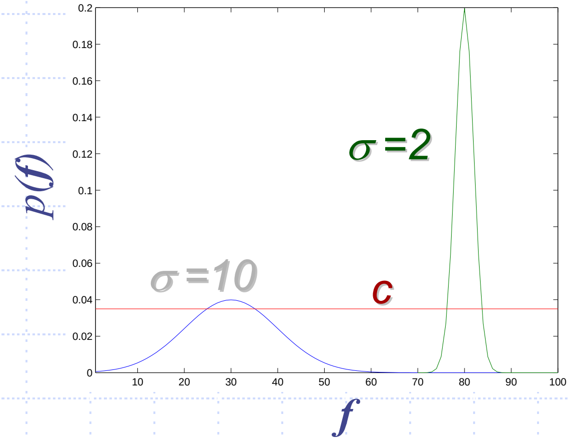
What We Are Doing…

- Approaches:

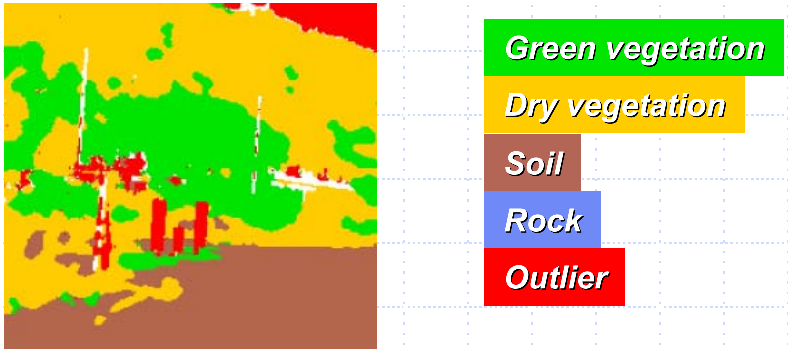
f is an outlier if $p(\mathbf{f}) < c$

- <u>What's the correct threshold c?</u>

  Just fix $P_o = P(\textit{outlier})$ and find c such that



- Solution: Monte Carlo integration



What We Are Doing...

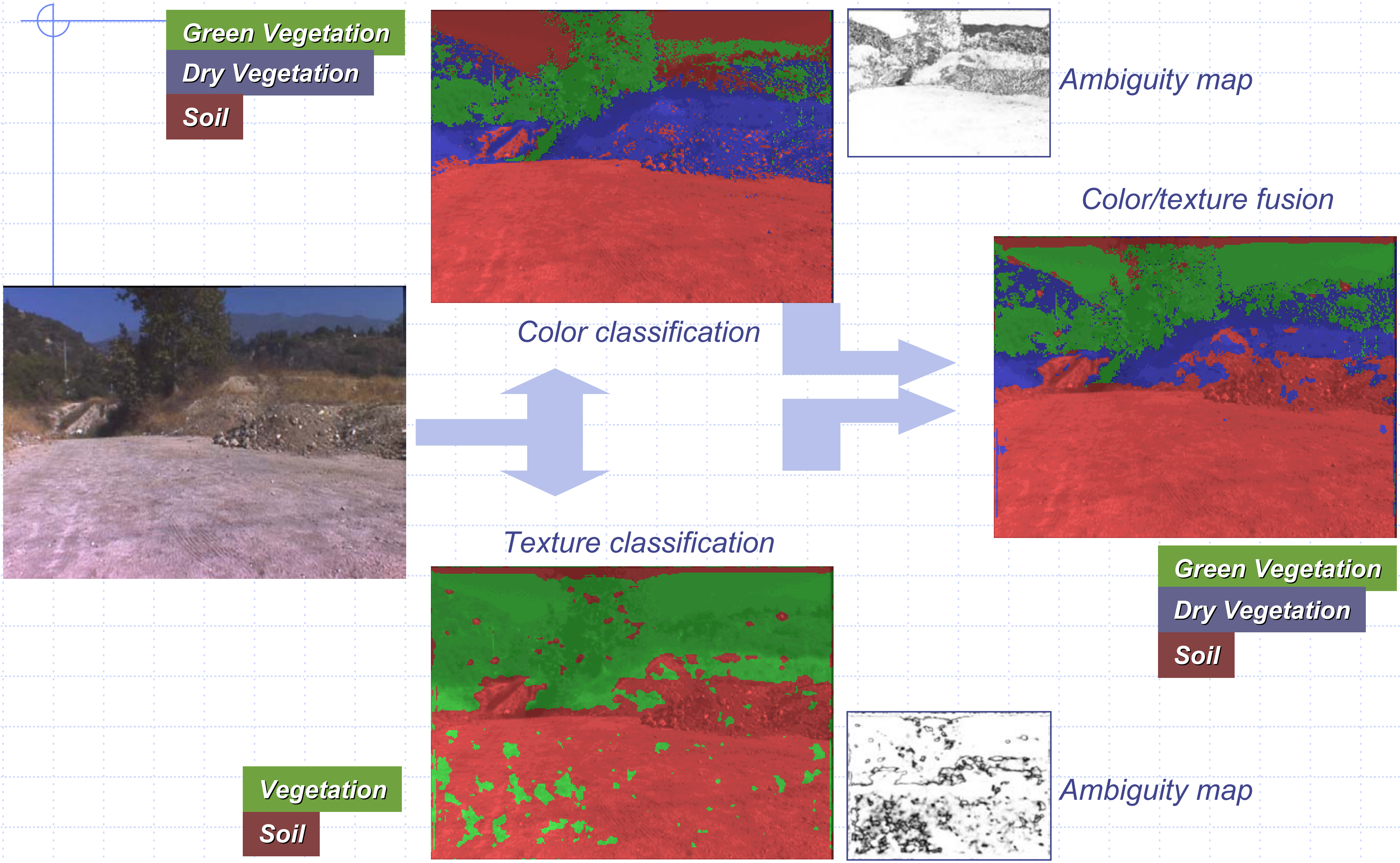
- The Monte Carlo integration

  We need to find a suitable threshold c, so that $P = \int_{p(f)>c} p(f)df$

  The solution is

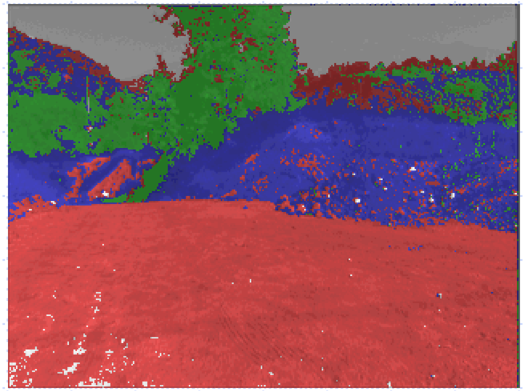
$$\int_{p(f)>c} p(f)df = \int_{-\infty}^{\infty} p(f)\delta(p(f)>c)df = \underset{p(f)}{E}[\delta(p(f)>c)] = \frac{\#samples(p(f)>c)}{\#samples}$$

Experiment Result



Experiment Result

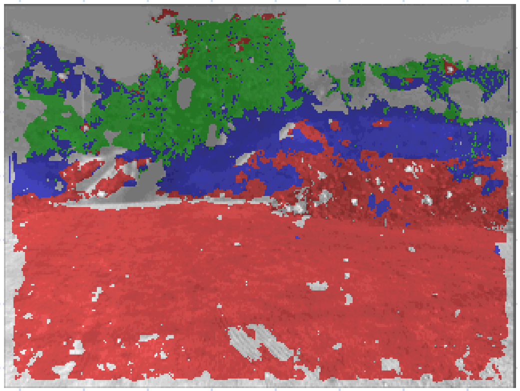
Green Vegetation
Dry Vegetation
Soil



Color classification

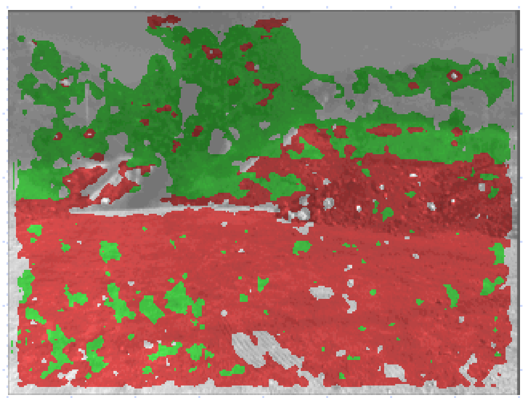
Ambiguity map

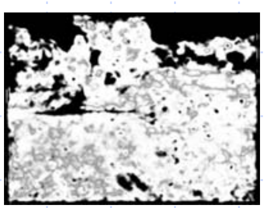
Color/texture fusion



Green Vegetation
Dry Vegetation
Soil

Texture classification





Ambiguity map

Vegetation
Soil

Future Work

- What's the difference between $p_{12}(f_1, f_2|j)$ and $p_1(f_1|j)p_2(f_2|j)$

Two approaches: cross-correlation, mutual information(KL distance)

The definition of mutual information:

$$KL[p_{12}(f_1,f_2), p_1(f_1)p_2(f_2)] = \iint p_{12}(f_1,f_2)\log\frac{p_{12}(f_1,f_2)}{p_1(f_1)p_2(f_2)}df_1df_2$$

$$= -H_{p_{12}} + H_{p_1} + H_{p_2}$$

Future Work

- If $p_{12}(f_1, f_2|j)$ and $p_1(f_1|j)p_2(f_2|j)$ are not equal, what will be the expect cost if we assume the conditional independence hold?

Reference

- Bayesian feature fusion for visual classification, Roberto Manduchi.
- On combining classifiers, Josef kittler.
- A weighted combination of classifiers employing shared and distinct representations, J.Kittler.

Thanks!