

Learning Object Detectors for Panchromatic Imagery



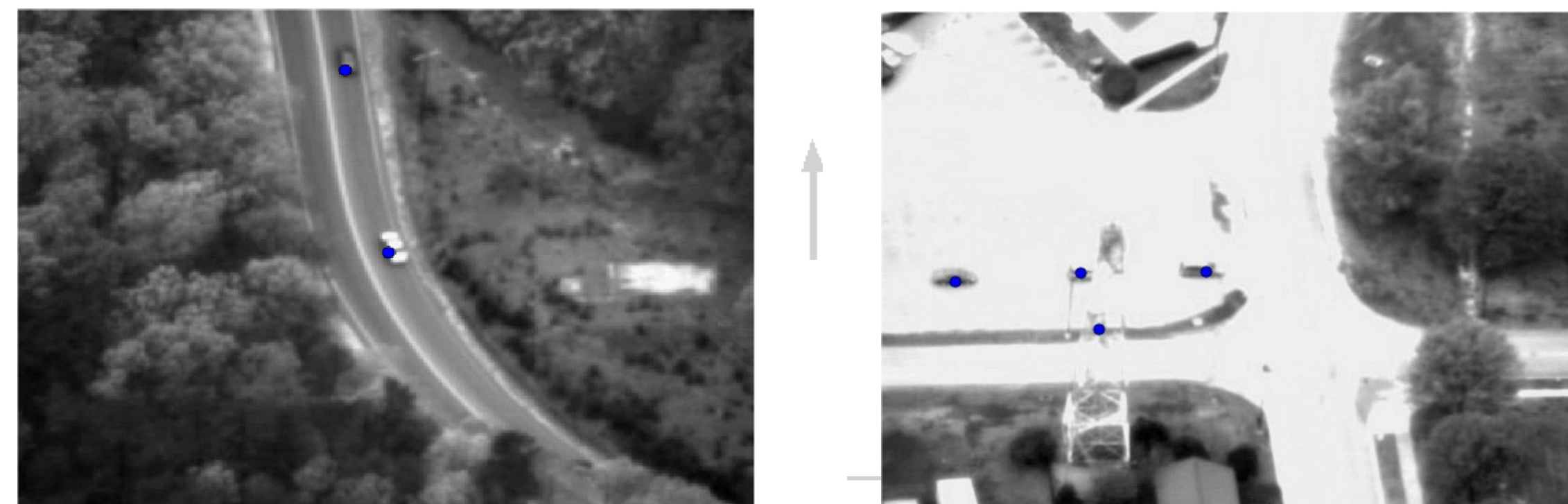
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Abstract

Detecting objects in single band imagery is often a challenge due to a lack of a smooth feature response on the object and a flat feature response elsewhere. Rich features are often needed. We consider an approach for building an ensemble of weak pixel classifiers on automatically generated features. These features are represented by a directed graph of image processing filters. We evaluate our approach on a data set of panchromatic imagery acquired from an aerial sensor.

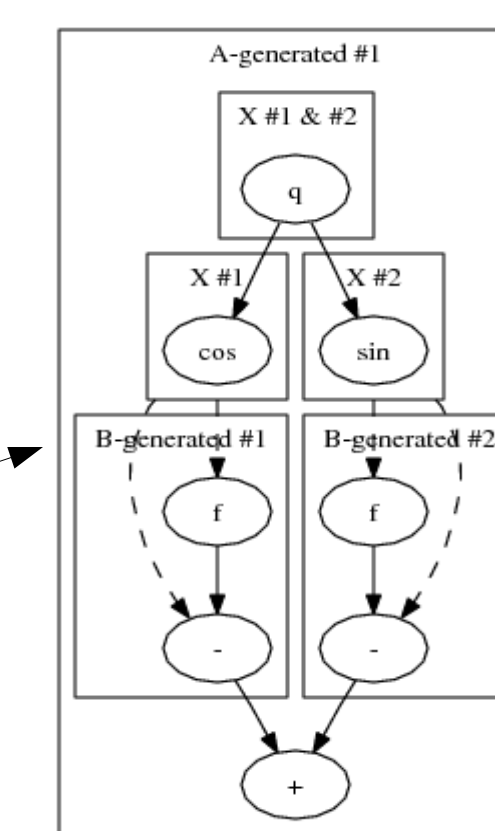


We used the VIVID data set for our experiments. This data set consists of 206 black-and-white images taken from multiple altitudes and aspect angles. Each image is resampled to a common Ground-Sample-Distance (GSD) to eliminate the need for scale-invariance in feature extraction and object detection. The objects of interest are cars and trucks.

Grammars

Features are generated by a generative, context-sensitive grammar called a Feature Grammar. These grammars define a sensible set of graph-based compound features.

Example Algorithm Generated



A Simple Grammar

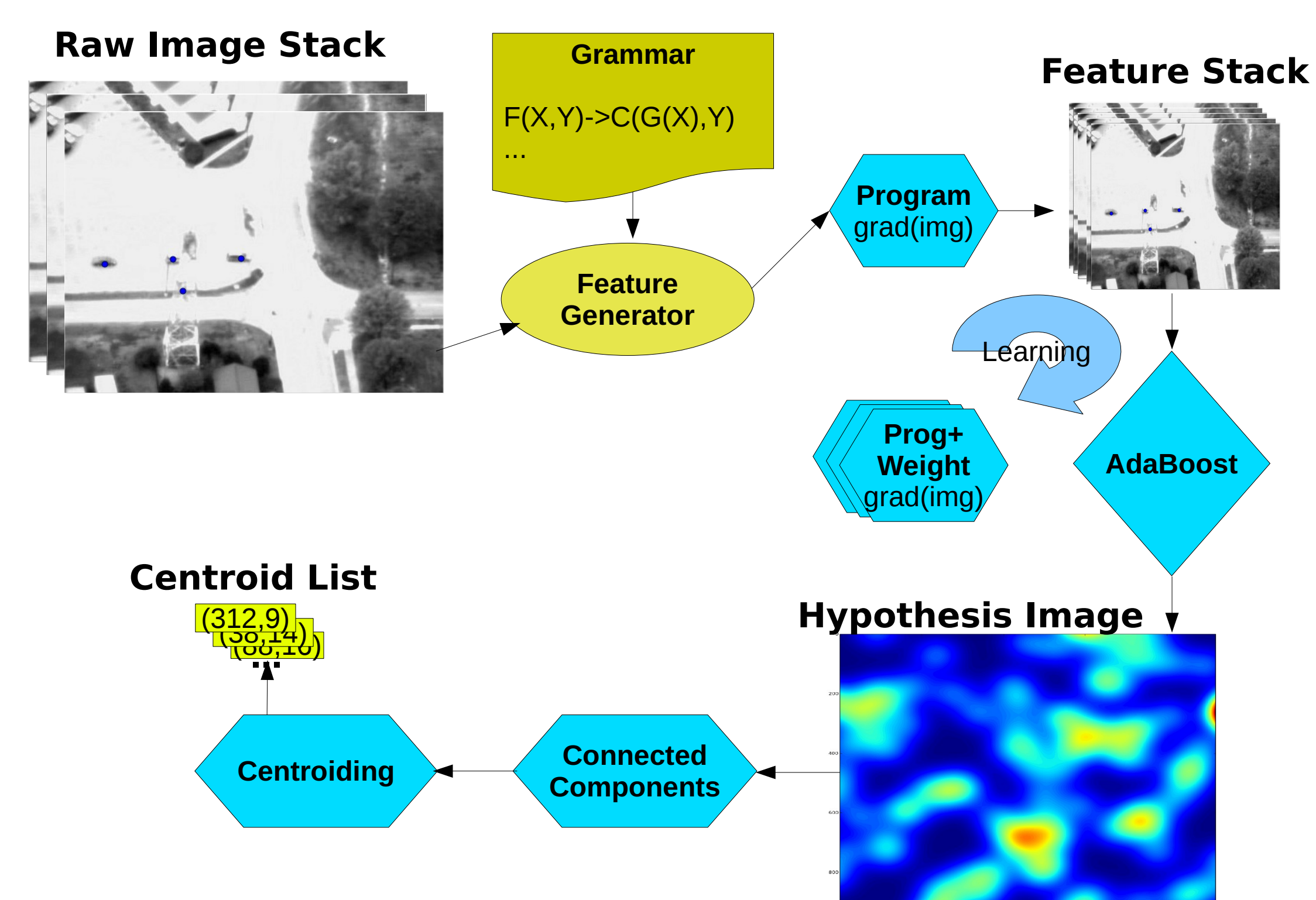
$A() \rightarrow B(\cos(q)) + B(\sin(q))$
 $B(X) \rightarrow f(X) - X$

Image Feature Extraction Grammar

```

Feature() -> NonLinearBinary(UnaryFeature(PanBand()), UnaryFeature(PanBand()))
           | NonLinearUnary(UnaryFeature(PanBand()))
RandomSE() -> structure_element(? (rand()*pi), ? (rand_ab(3,30)), ? (10** (rand()*2-1)))
PanBand() -> img
NonLinearBinary(X, Y) -> mult(X, Y) | normDiff(X, Y)
LinearBinary(X, Y) -> scaledSub(X, Y) | blend(X, Y)
Binary(X, Y) -> NonLinearBinary(X, Y) | LinearBinary(X, Y)
Unary(X) -> LinearUnary(X) | NonLinearUnary(X)
Combine(X) -> Unary(X) | Binary(X, Combine(PanBand())) under {wt: 0.3}
UnaryFeature(X) -> Combine(X)
NonLinearUnary(X) -> sigmoid(X, ? (sigmoid_rand_a()), ? (sigmoid_rand_b()))
           | ptile_structured(X, ? (rand() * 100), RandomSE())
           | gaussgradmag(X, ? (rand_snorm() * 3))
LinearUnary(X) -> viola(X, ? (rand(10 ** 8)))
           | laws(X, ? (rand(25)))
           | laplace(X, ? (rand_snorm() * 3))
           | gabor(X, ? (rand()*pi), ? (rand()*30+1), ? (10** (rand()*2-1)),
           | ? (rand() * 10 + 3), TrigFun())
TrigFun() -> cos | sin
    
```

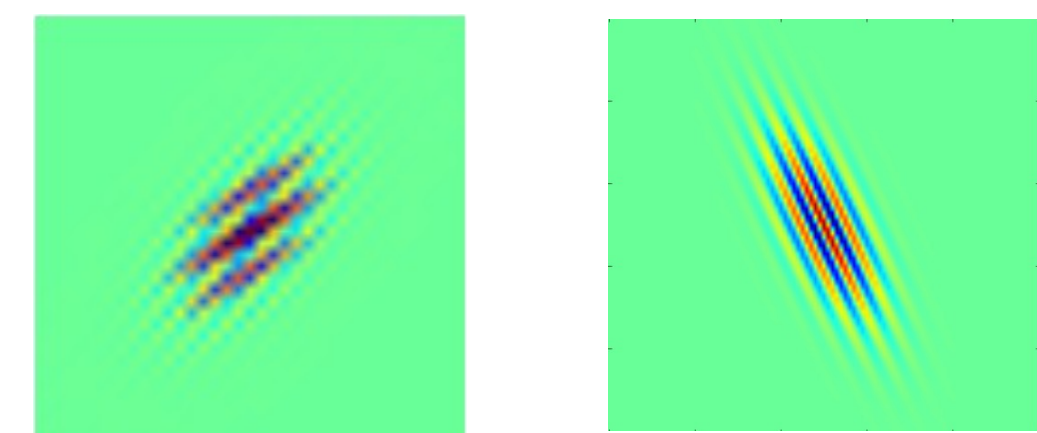
Basic Approach



AdaBoost produces a set of weak pixel classifiers. To predict object locations, we threshold this voted hypothesis, find the connected components, and use the center of masses as locations. Smoothing the hypothesis image, region growing it, then using KDE to filter hits helps reduce false alarms.

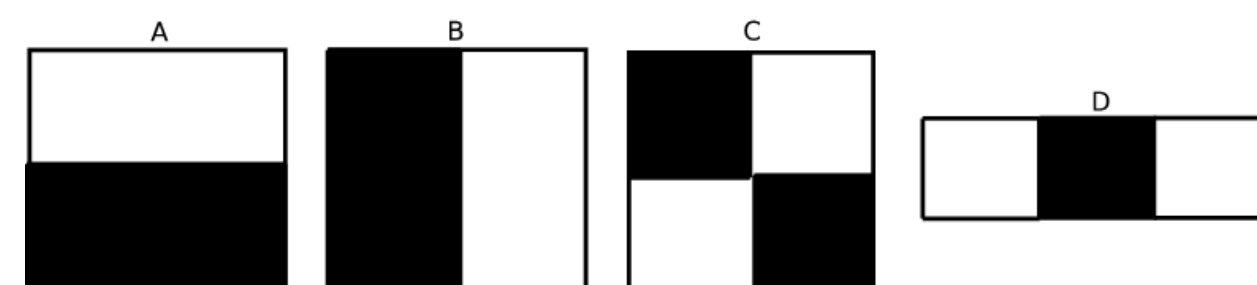
Features

Gabor Filters

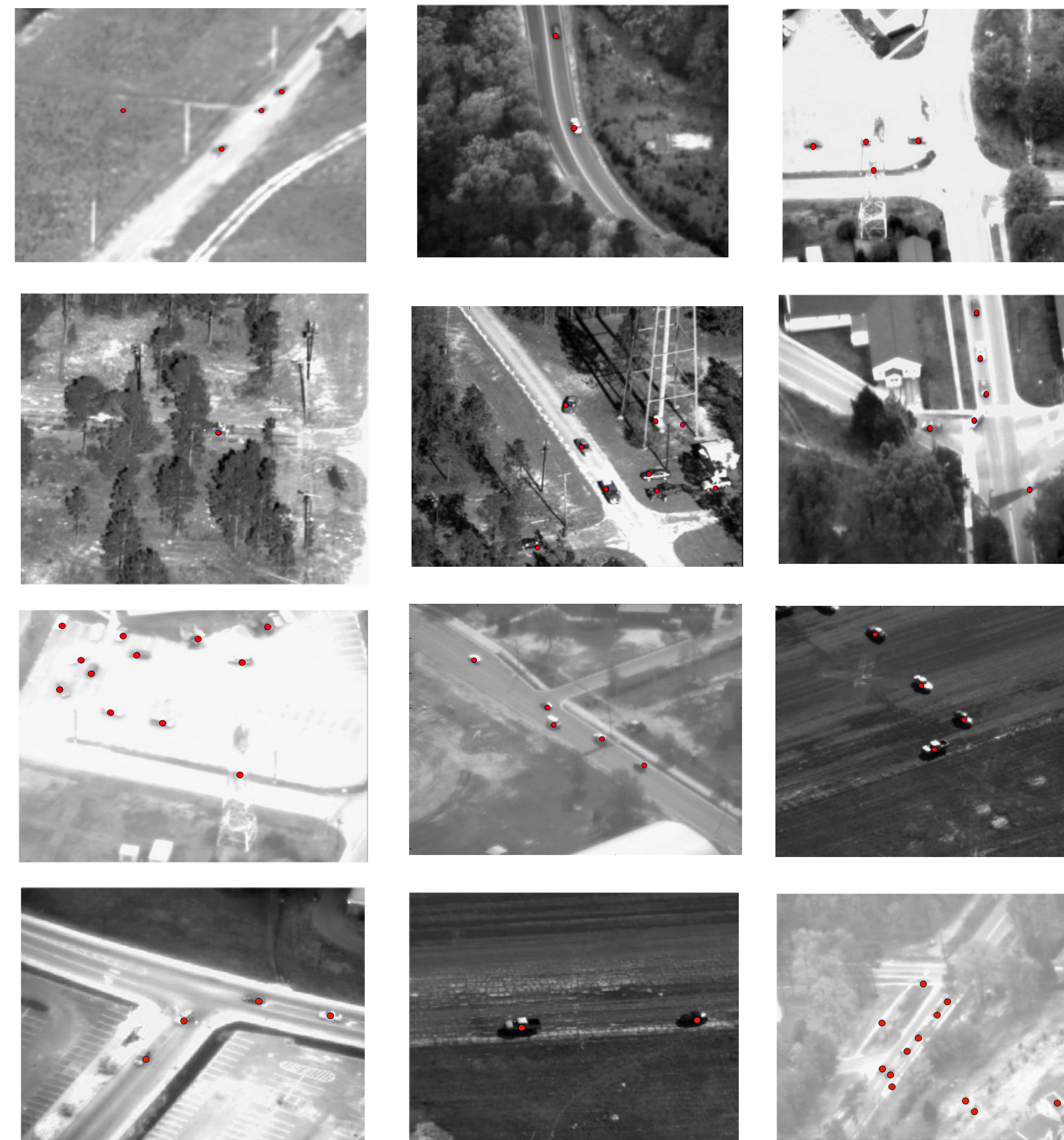


- Other Features:
- Edge Detectors
 - Laws Texture Energy Measures
 - Gray-scale Morphology
 - Percentile Filters
 - Sigmoid

Haar Feature Primitives



Out-of-Sample Results



Work In Progress

- Object detection without segmentation: ensemble of weak detectors, each generating (x,y) pairs.
- Noise-robustness without smooth feature responses.