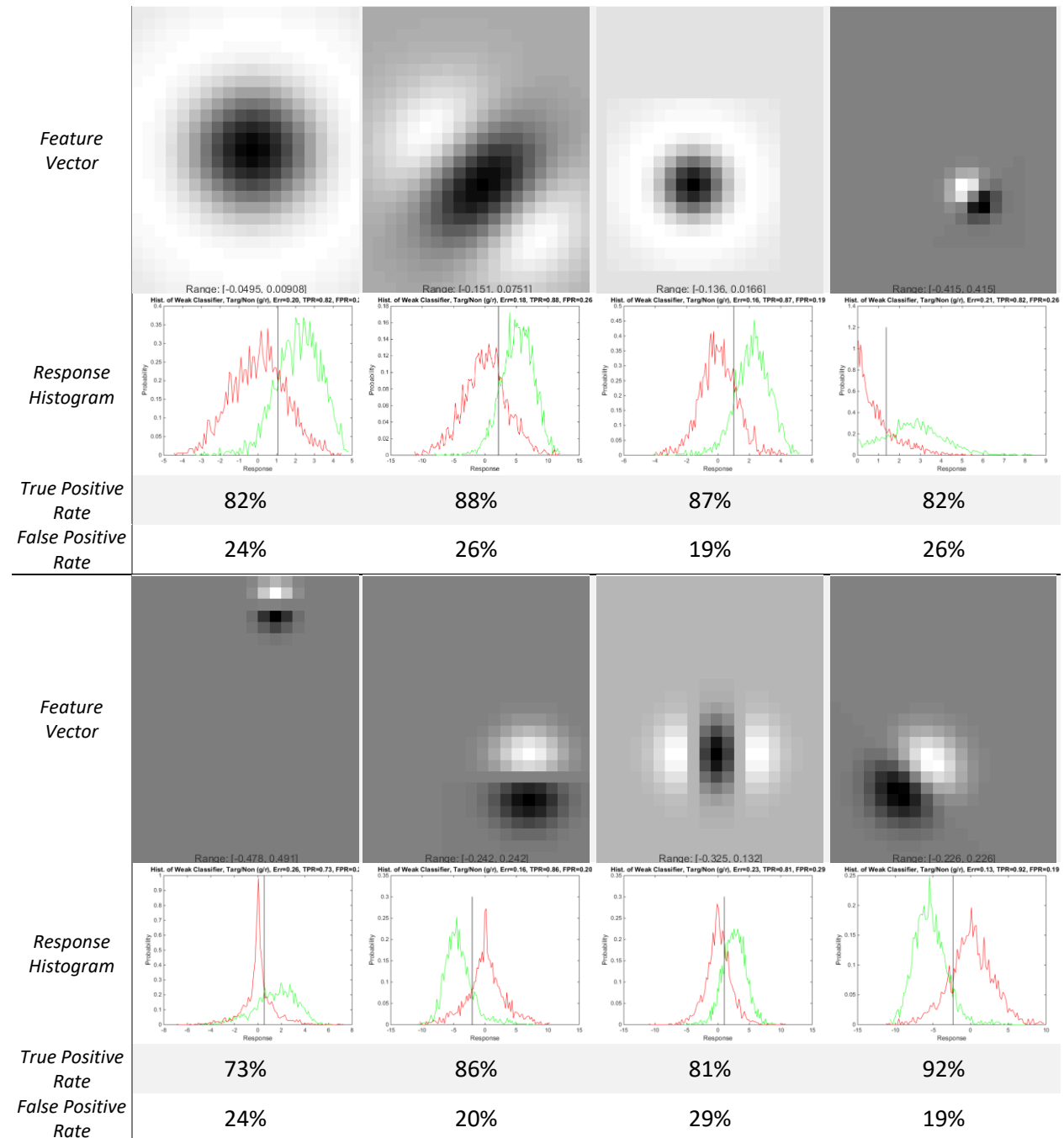


Assignment 4 Report

Detecting Human Eyes

Weak Classifiers

Result



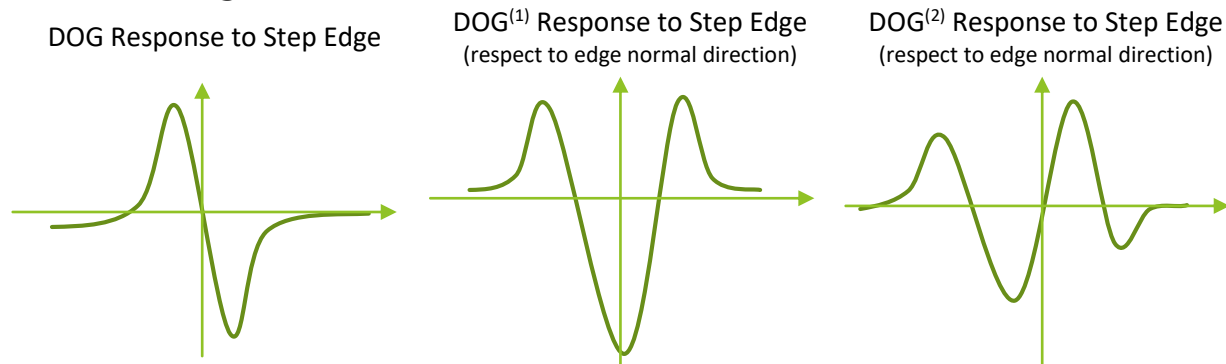
Ada-Boost

Corresponding Feature to Structures

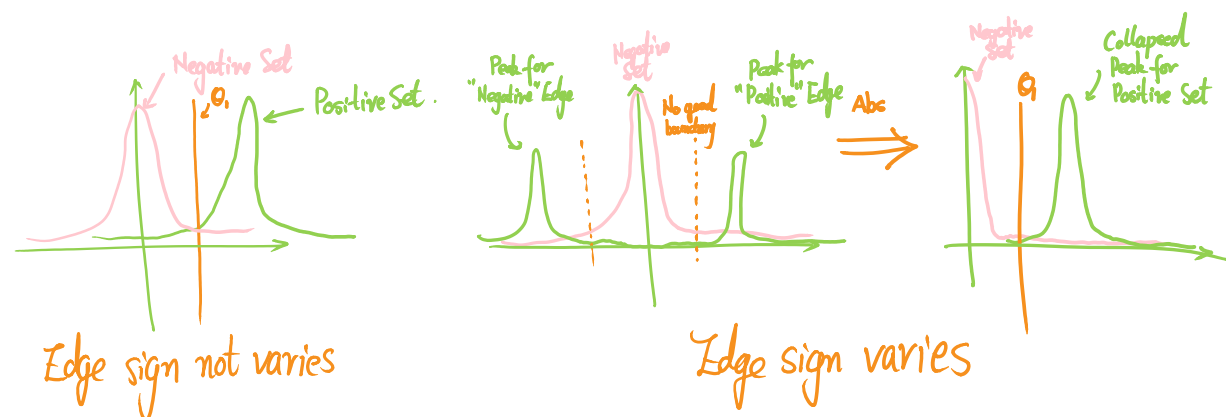
Assumption to negative set

The feature is determined by the difference of positive and negative set, here all the discussion is under the assumption of negative set have a **strongest response at 0 to all the 0, 1st and 2nd order derivative of DOG filter** (at all the position, scale and orientation).

Feature to edge



If the sign of the (step) edge stays mostly constant, then an **1st order derivative DOG filter (feature)** match the position, scale and orientation will most likely to be selected. As shown above, the response of 1st order derivative of DOG along the edge normal direction gives strongest response at the edge center. For positive set, it will result in one peak far from zero in the response histogram, thus separate the negative set and positive set. If the peak is showed in the positive X direction, the parity attribute of the feature will be negative (-1), while the negative peak result in positive parity (+1).



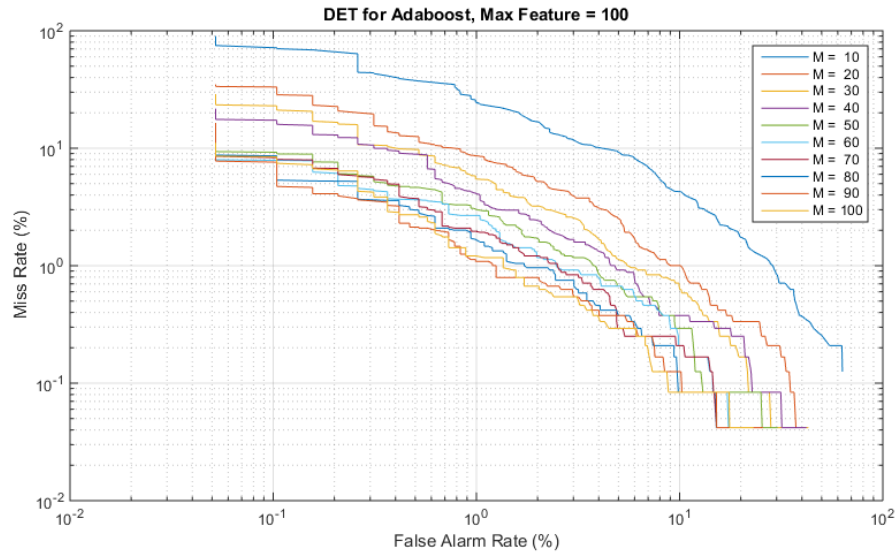
If the sign of (step) edge varies, then the **Absolute value** of the corresponding **1st order derivative DOG filter** will most likely to be selected. There will be two expected peak for positive training set in the response histogram without extracting the absolute value, and this two peak will be symmetry to each other respect to Y-axis. Using the absolute value operator will collapse the two symmetric peak into one and achieve the similar separation effect.

Feature to relative smooth region

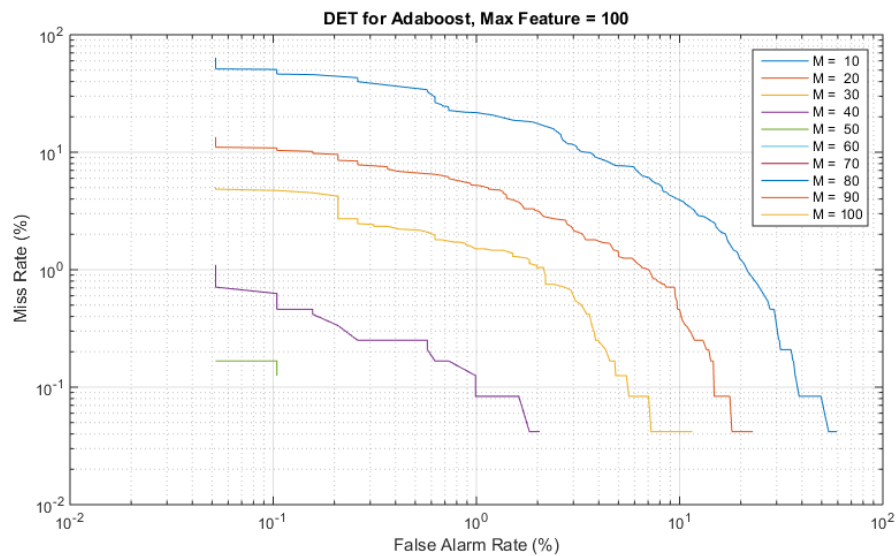
If the area is relatively smooth, than all the DOG filter (0, 1, 2 derivative) will still get very weak response (almost zero) and thus positive set will have a peak at zero, **cannot** be differed from the negative set. In this case, **No good feature in DOG filter space.**

DET Curves

Test Set



Training Set



* DET curve for $M \geq 60$ is 0% Miss rate and 0% False alarm rate thus cannot be showed in log-log plot.

Comments

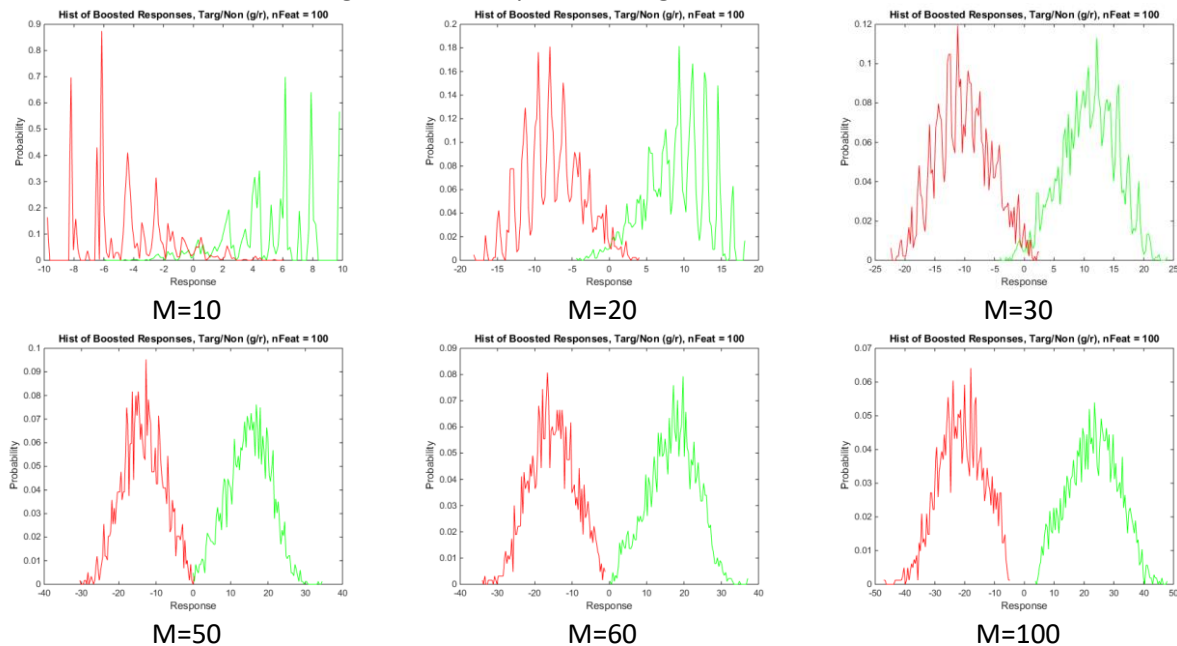
In general, they are quite good when $M \geq 50$.

Apparently, the strong classifiers have better performance in training set than testing set in all the cases, since the training set is just a sample of the testing set, and our classifier is trying to determine the boundary to separate the positive set and negative set in training data. And the boundary in testing data may not be identical (but should be similar) to the boundary in training data, thus we will have better result in training data set.

For $M = 10$ to 30 , the difference between training set and testing set is not such significant. In this phrase, the feature we extract from the training is not even a complete description of the boundary in training data set.

For $M = 40$ and above, the difference between training set and testing set is much significant, the strong classifier defined boundary basically separated the positive set and negative set completely, but this cannot result in significant performance improvement in testing set since the limitation of training data is affecting the accuracy.

Strong Classifier Response Histogram Evolution with M



Application to an Image Patch

Result (100 Features, threshold = 19, patch = whole image)

