University of Toronto

Detecting Human Eyes

CSC2503 Fall 2014
Foundations of Computer Vision

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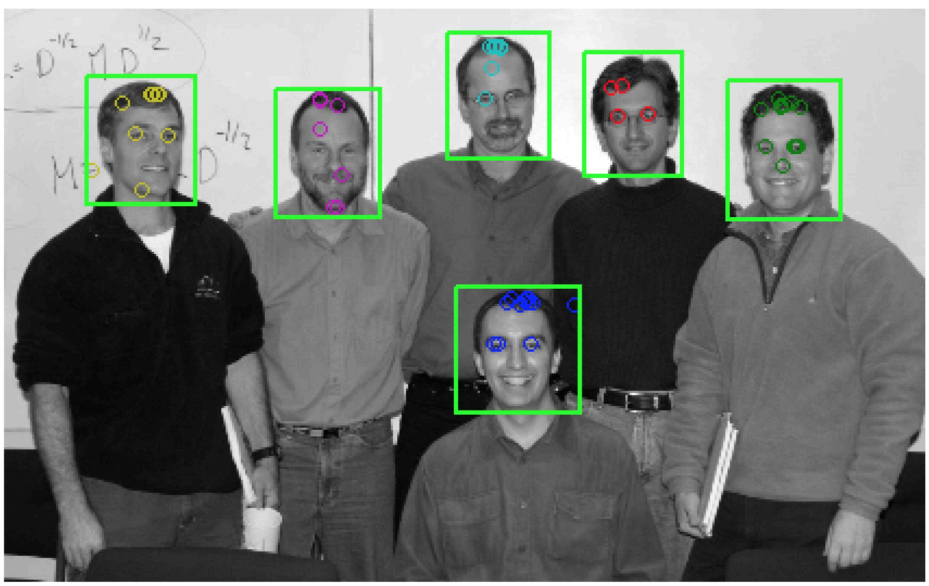

December 9, 2014

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1 Weak Classifiers

In order to find the optimum parameters $\vec{\theta}$ for the weak classifier, the error in Equation 1 must be minimized. Minimal error occurs when $I(y_k \neq h(\vec{x}_k, \vec{\theta})) = 0 \implies y_k = h(\vec{x}_k, \vec{\theta})$

$$err = \frac{\sum_k w_k I(y_k \neq h(\vec{x}_k, \vec{\theta}))}{\sum_k w_k} \tag{1}$$

We want to find $h(\vec{x}, \vec{\theta})$ with the least errors. Each response, $r = u(\vec{f}^T \vec{x})$, is sorted, and the class labels, y_k, are adjusted according to weights, $\vec{w}$. The optimum parameters, $\vec{\theta}$, are determined by checking all possible combinations of threshold θ_1 and parity θ_2 values. Then, the optimum θ_1 and θ_2 are chosen based on the combination that results in the least misclassified samples. An example of this method is illustrated below.

Example:

$$\vec{w}.*\vec{y} = \begin{bmatrix} 0 & 1 & 0 & 1 & 1 \end{bmatrix}$$

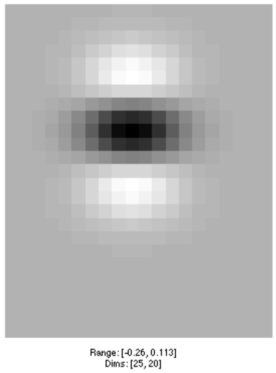
For $\theta_2 = 1$:

Threshold θ_1	**Misclassified Samples**
1	$1+3=4$
2	$1+2=3$
3	$2+2=4$
4	$2+1=3$
5	$2+0=2$

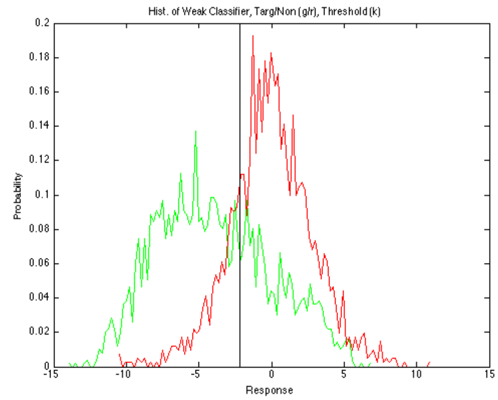
For $\theta_2 = -1$:

Threshold θ_1	**Misclassified Samples**
1	$\boxed{0+1=1}$
2	$1+1=2$
3	$1+0=1$
4	$2+0=2$
5	$3+0=3$

From the above example, the minimum misclassified samples occurs at the parameters $\vec{\theta} = \begin{bmatrix} \theta_1 = 1 & \theta_2 = -1 \end{bmatrix}^T$. A general approach is implemented in MATLAB for any $\vec{w}$ and $\vec{y}$ using the `cumsum` and `min` functions to avoid `for` loops. Results of the histogram of different weak classifiers are shown in Figure 1-4. The probability of a sample with the target is displayed in green and without the target is displayed in red. If the classifier's optimum parity is 1, the target response is likely to be less than the threshold, and non-target response is likely to be greater than the threshold. Likewise, if the the classifier's optimum parity is -1, the target response is likely to be greater than the threshold, and the non-target response is likely to be less than the threshold. True positive and false positive rates are reported in the caption of each figure. Figures 1,3,4 show a stronger response and have lower false positive rates as their histograms of target and non-target response are more distinct compared to that of Figure 2.

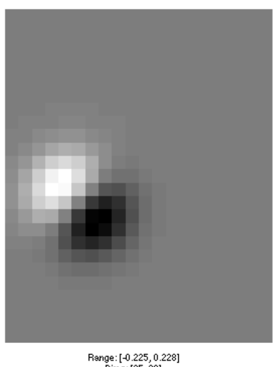


(a) Derivative of Gaussian kernel

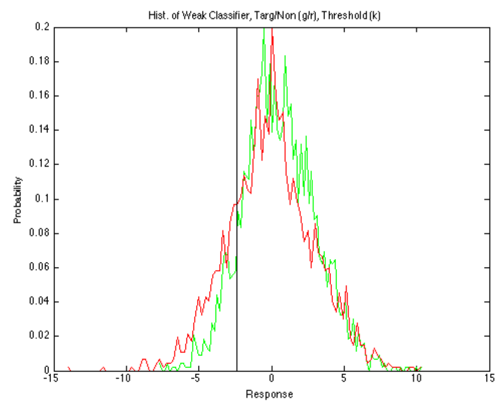


(b) Histogram response

Figure 1: $\theta_1 = -2.2004$, $\theta_2 = 1$, True Positive Rate = 37.39%, False Positive Rate = 8.77%

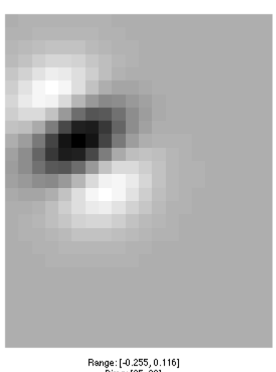


(a) Derivative of Gaussian kernel

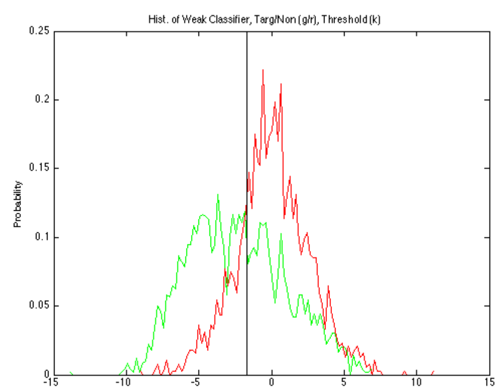


(b) Histogram response

Figure 2: $\theta_1 = -2.3875$, $\theta_2 = -1$, True Positive Rate = 49.32%, False Positive Rate = 35.28%

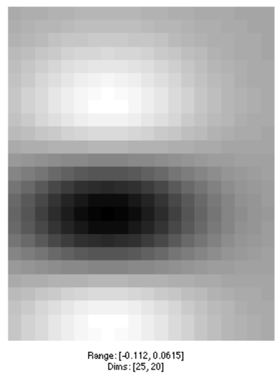


(a) Derivative of Gaussian kernel

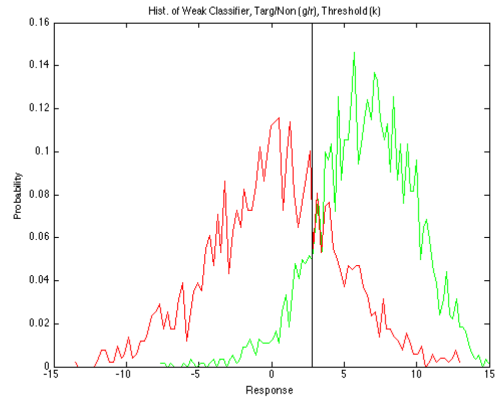


(b) Histogram response

Figure 3: $\theta_1 = -1.7229$, $\theta_2 = 1$, True Positive Rate = 32.75%, False Positive Rate = 9.51%



(a) Derivative of Gaussian kernel

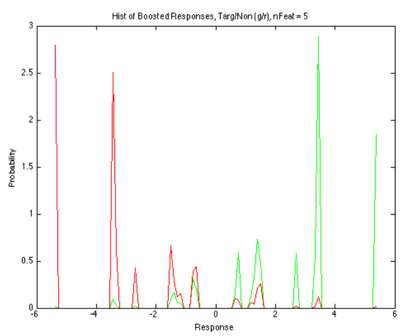


(b) Histogram response

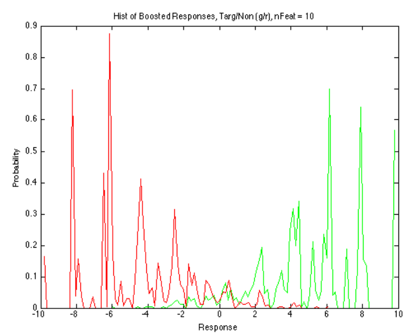
Figure 4: $\theta_1 = 2.8197$, $\theta_2 = -1$, True Positive Rate = 48.50%, False Positive Rate = 12.02%

2 AdaBoost

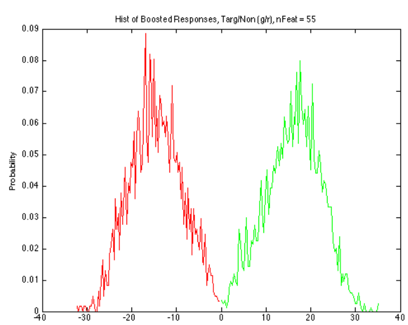
Figure 5 shows the histogram of boosted responses during training. As each weak classifier is added, the histogram response becomes stronger, and we get better distinction between targets and non-targets. As the training process continues, the true positive rate grows, and the false positive rate reduces.



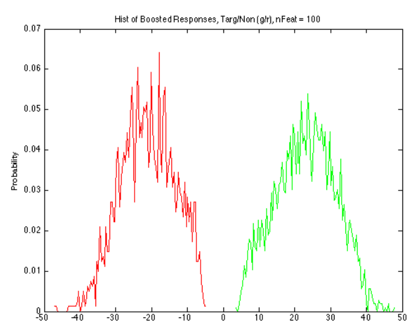
(a) nFeat=5



(b) nFeat=10



(c) nFeat=55



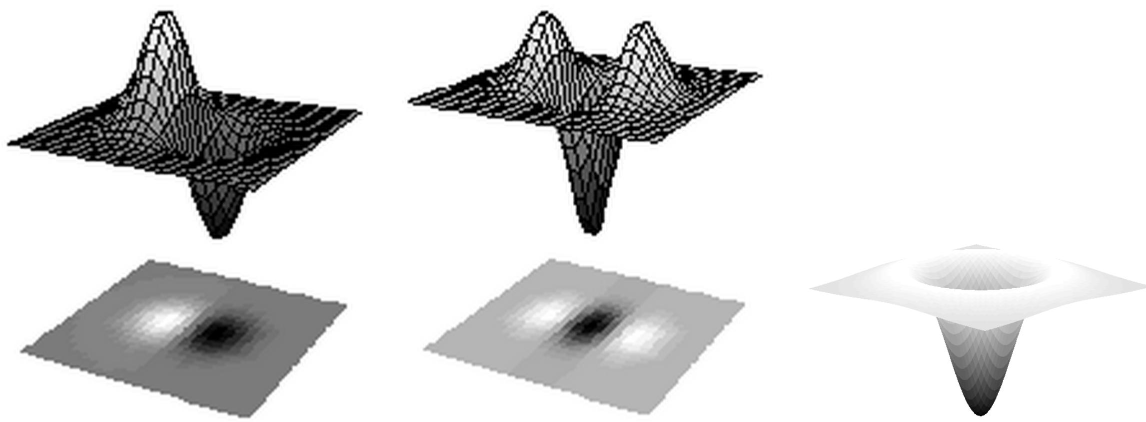
(d) nFeat=100

Figure 5: Histogram of boosted response for increasing number of features for training set

If there is an edge in most of the training target images at a particular scale, sign, and orientation, the selected feature is expected to be the first derivative of Gaussian as that will indicate an edge perpendicular to its orientation.

If the sign of the edge varies (i.e., light to dark or dark to light), the selected feature is expected to be the absolute value of the first derivative of Gaussian. The absolute value will account for sign changes of the derivative from image to image.

If the training target images are all relatively smooth (i.e., no edges) in a particular region, the selected feature is expected to be the absolute value of the second derivative of a Gaussian. Second order Gaussians provide texture information and stronger response in intensity changes. Peaks result in strong positive response, valleys result in strong negative response, and smooth regions result in near zero response. The absolute value combines the positive and negative responses for a stronger response, which will distinguish this from smooth regions.



(a) 1^{st} derivative (b) 2^{nd} derivative (c) Laplacian (2^{nd} order)

Figure 6: Gaussian filters

Figures 7-8 shows the DET curves for various number of weak classifiers, M, for both the training set of eyes and non-eyes, and the test set. Training does not need to be re-run to evaluate the strong response for some M less than the maximum number of features trained because we can just limit the sum of weak classifiers to the first M terms. As seen in the DET curves, there is a tradeoff between miss rate (false negative) and false alarm rate (false positive). For low M values, both the test and training set have similar corresponding DET curves and it can be seen that they do not perform well. As M increases, performance of the strong classifier becomes better as both the miss rate and false alarm rate decreases. Howerever, for high M values, the DET curves of testing and training are not the same. Moreover, it can be seen that the training set converges quickly to perfect accuracy. This is because the classifier is trained on the training set, so high M classifiers should have near-perfect (or perfect) detection rates. There will always be some error for the test set as the classifier cannot capture all possible variations of eye appearances. Thus, the DET curves for test sets have higher errors for the same high M value as the training set.

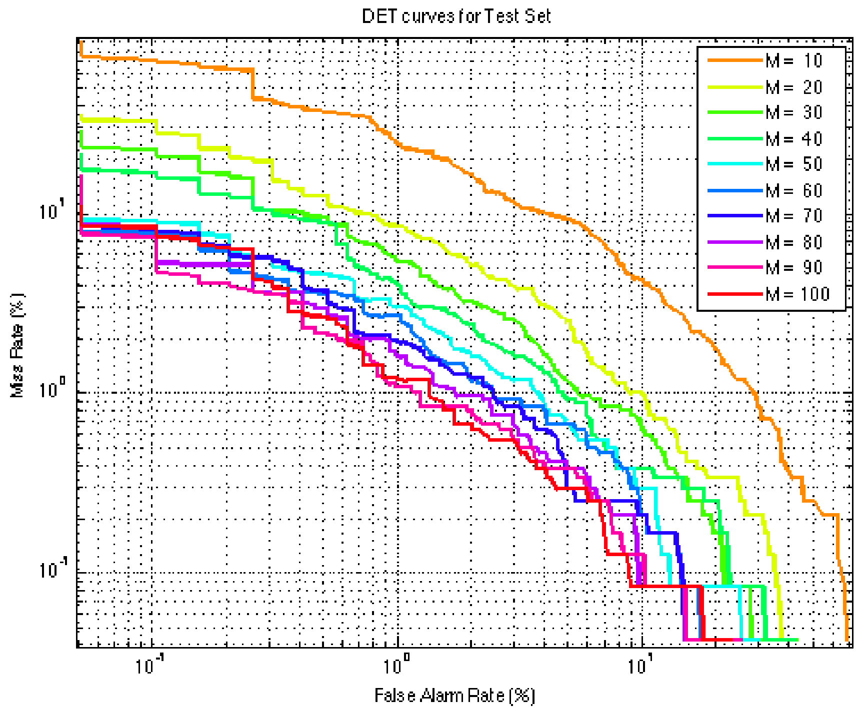


Figure 7: DET curves for Test Set

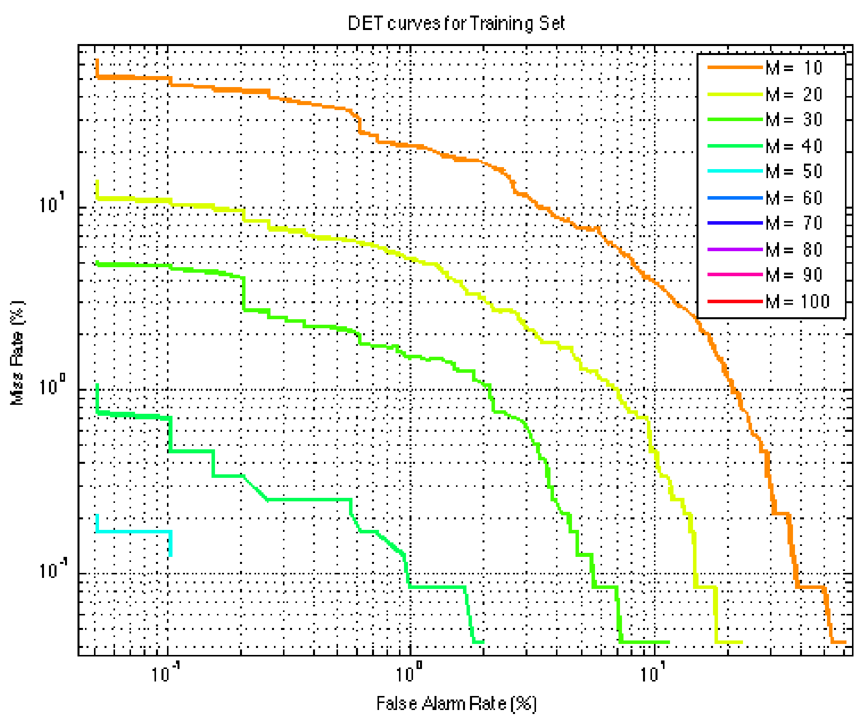


Figure 8: DET curves for Training Set

3 Application to an Image Patch

Figure 9 shows the eye detector on a new example image not present in training or test sets. There are many false positives even with a high threshold. This is due to regions with similar appearances, such as the hair. The algorithm can be improved by training with negative examples to reduce the number of false positives.

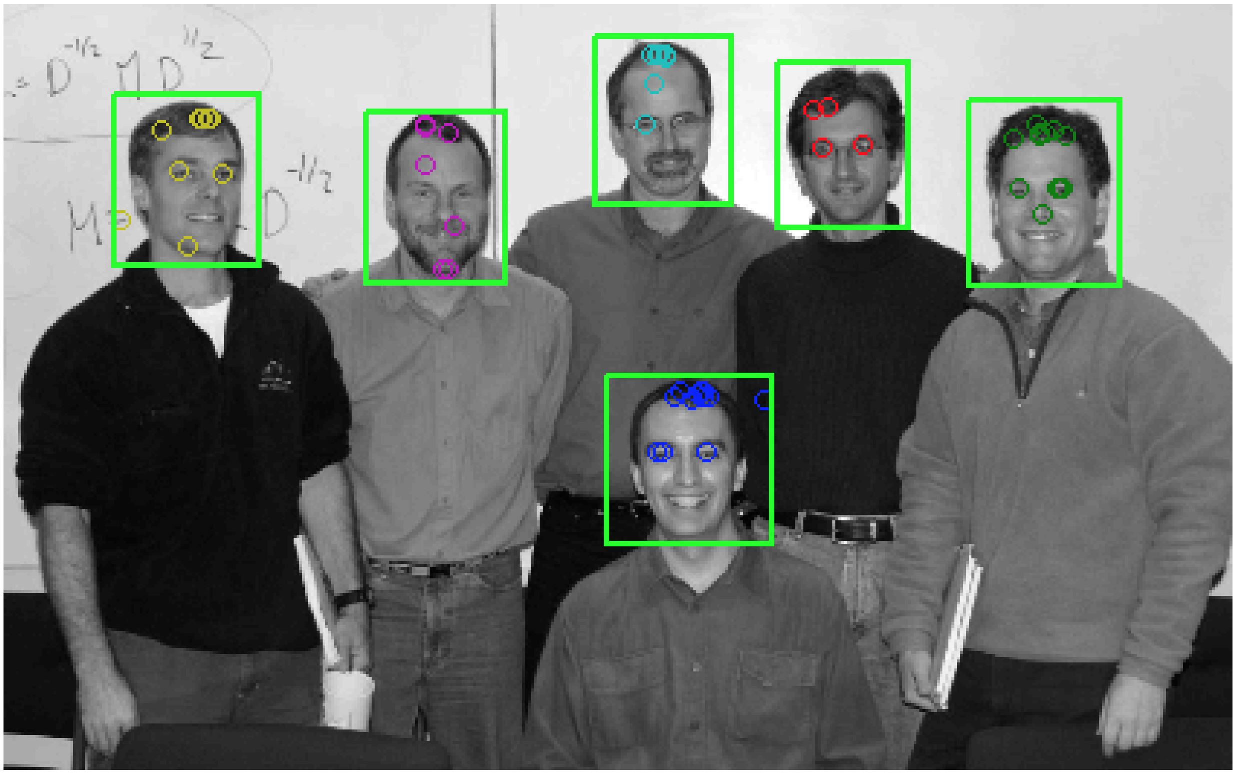


Figure 9: Resulting detections overlayed on top