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Texas A&M University

Electrical and Computer Engineering Department

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Project Report

Face Detection using AdaBoost and Haar Features

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Aggie Code of Honor

An Aggie does not lie, cheat or steal or tolerate those who do.

Abstract

The main focus of the project is the implementation of the Viola-Jones Algorithm. The algorithm was a breakthrough in the field of face detection because it provided computationally feasible and accurate results. The algorithm uses a Haar features and Adaboost algorithm using a decision stamp classifier to perform the classification. In the project, we are extracting 5 different types of features types from 19 by 19 images. Then implement the Adaboost algorithm on the features to perform the classification of the image. Finally, the classifier error definition is changed to consider only the case of False-negative and False positives.

Features extraction

Haar Features

Table 1 (Feature Count)

Type 1 (Horizontal Edge Detection)	7440
Type 2 (Vertical Edge Detection)	7440
Type 3 (Horizontal Line Detection)	3472
Type 4 (Vertical Line Detection)	3472
Type 5 (Four Feature detection)	3600
Total	25424

The feature size was limited by two constraints, one that area of the two black and white regions must be equal and the max size of the filter is 8 by 8. The computations were performed using an integral image to decrease computation time.

Type 1 Horizontal Edge Detector Sizes of m by n.

m = range[1,8], n =2* range[1,4]

Type 2 Vertical Edge Detector Sizes of m by n.

m = 2*range[1,4], n = range[1,8]

Type 3 Horizontal Line Detector Sizes of m by n

m = range[1,8], n = 4*range[1,2]

The smallest size has to be 1 by 4, to insure the we have 2 white pixels for 2 black pixels.

Type 4 Vertical Line Detector Sizes of m by n

m = 4*range[1,2], n = range[1,8]

The smallest size has to be 4 by 1, to insure the we have 2 white pixels for 2 black pixels.

Type 5 Four Feature Detector Sizes of m by n

m = 2*range[1,4], n = 2*range[1,4]

The smallest size has to be 2 by 2, to insure one pixel per area.

<u>AdaBoost</u>

Table 2 (Round Statistics)

Round	Empirical	False Positive	False negative	Feature Type	Strong Predictor accuracy
1	0.31813	0.09364	0.22449	Type 1	0.712
3	0.44498	0.07923	0.36575	Type 1	0.604
5	0.47539	0.09124	0.38415	Type 2	0.407
8	0.42497	0.17887	0.17967	Type 1	0.608
10	0.44458	0.08523	0.35934	Type 1	0.647

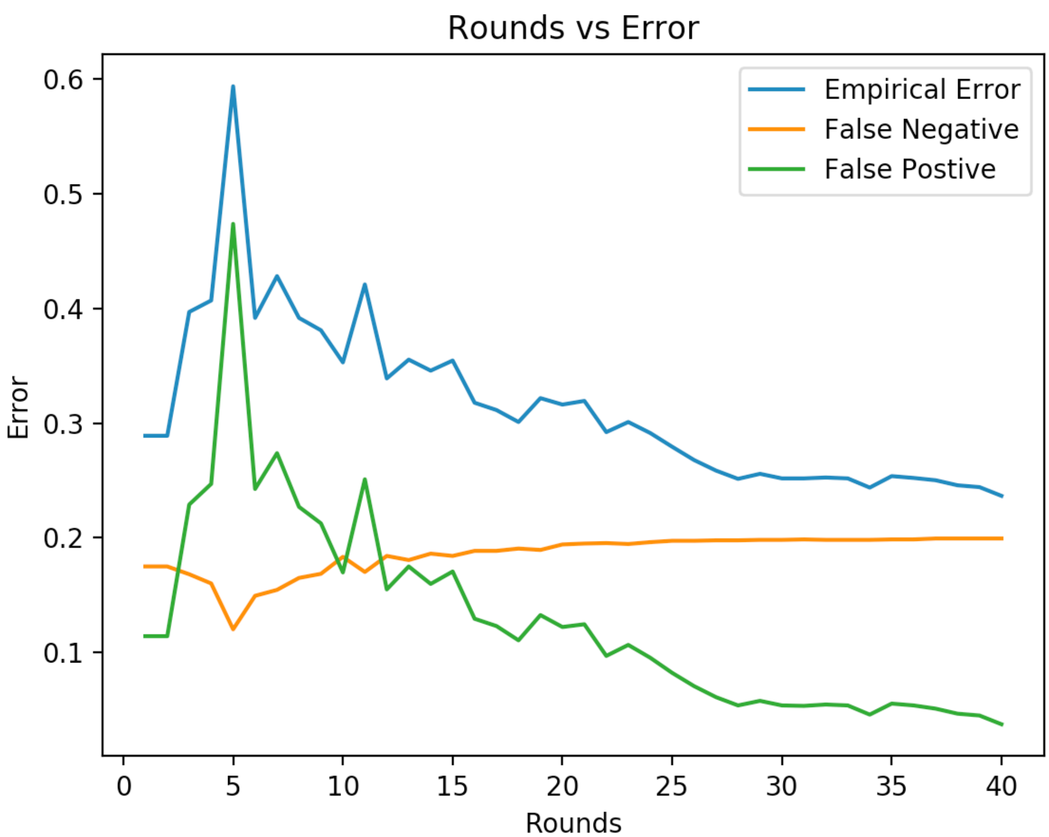

Figure 1 (Test errors over 40 rounds of ada boost)

The major focus of the classifier is on the false-positive error because the weight of the Ada boost is evenly distributed among the subpopulation of faces and non-faces. In the training data, there are only 499 images with faces and rest are all non-faces.

The weighted error of a false positive has a greater weight than false-positive error. The sample size is the culprit behind the increase in false-positive error. Round 1

(Type 1) Horizontal Edge Detection

M = 6

N = 1

Position = (0, 0)

Threshold = -85.5

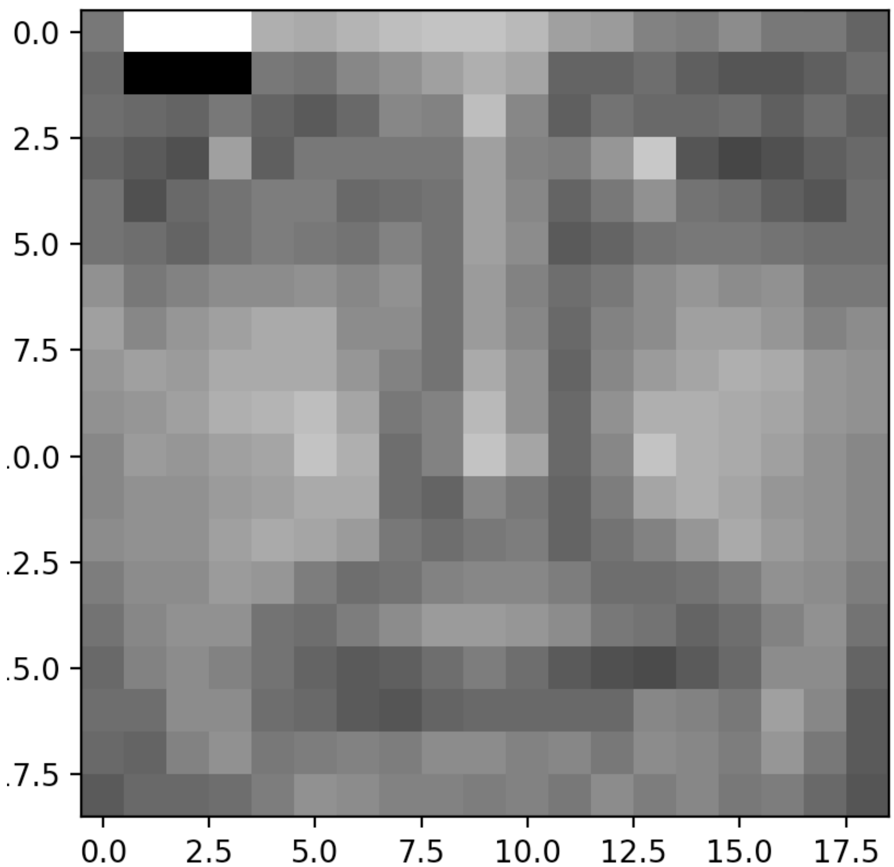

Figure 2(Round 1 features)

The feature is using the fact that a person's head is lighter than their eyebrows portion in the image. The alone was able to have an accuracy of 68.18%

Round 3

(Type 2) Vertical Edge Detection

M = 4

N = 1

Position = (9, 16)

Threshold = -18.5]

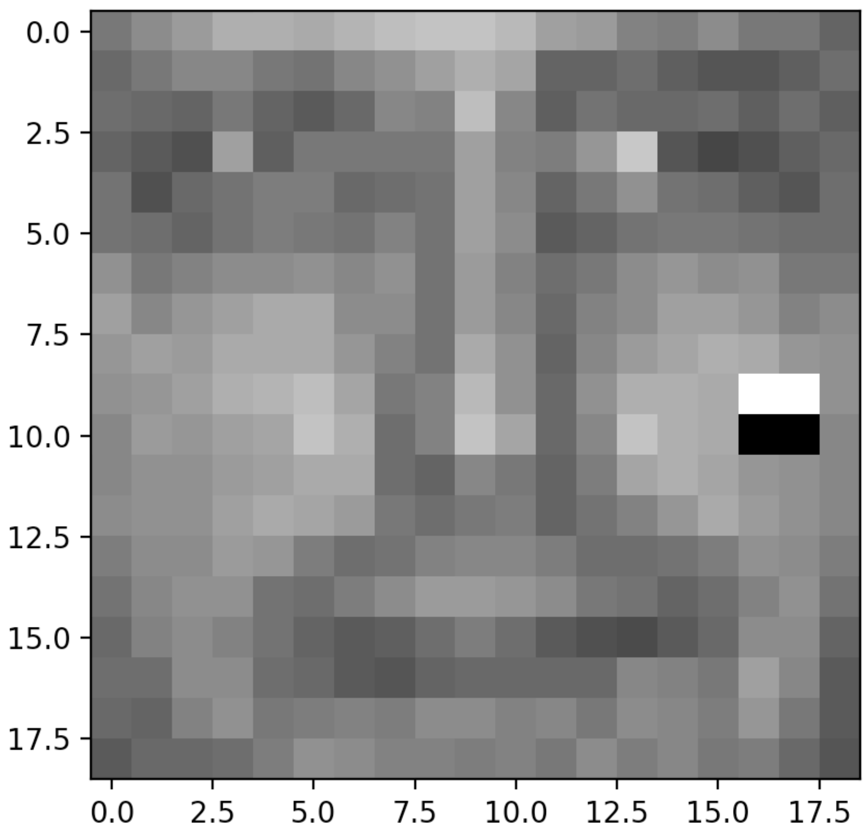

Figure 3(Round 3 features)

The feature is not a good classifying face in terms of false negative error, but it is good at determining non-faces, which leads to decreases in the false-positive error.

Round 5

(Type 2) Horizontal Edge Detection

M = 2

N = 2

Position = (9, 14)

Threshold = -16.5

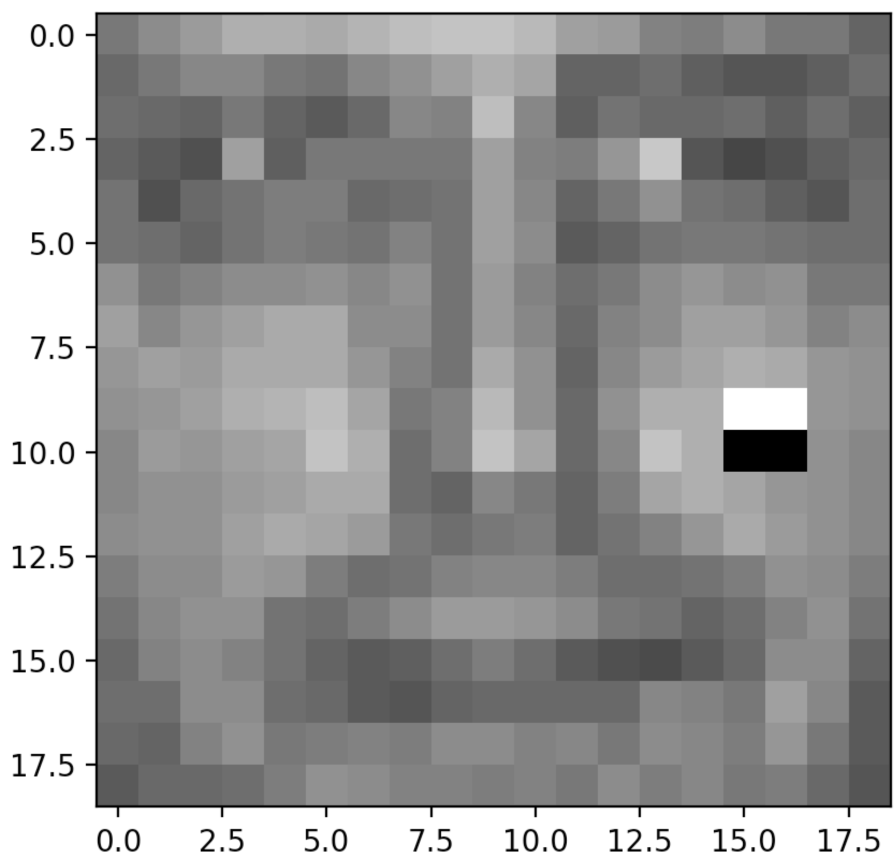

Figure 4(Round 5 features)

The feature is not a good classifying face in terms of false negative error, but it is good at determining non-faces, which leads to decreases in the false-positive error. By the addition of this feature, the strong classifier will low false positive error but an increase in the total error of the classifier.

Round 8

(Type 1) Horizontal Edge Detection

M = 4

N = 1

Position = (7, 16)

Threshold = -48.5

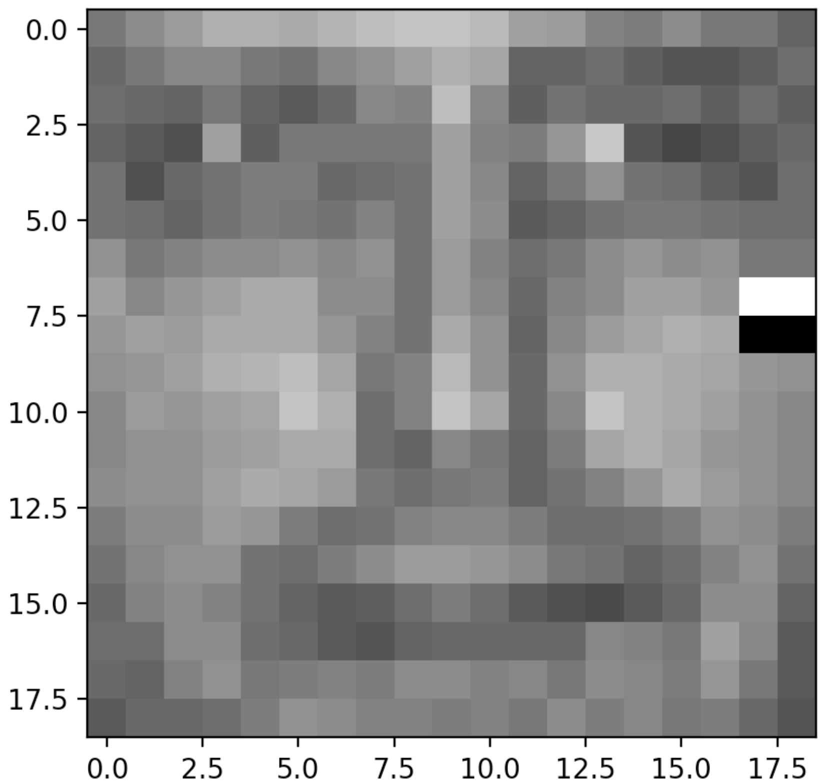

Figure 5(Round 8 features)

In round 8 of the algorithm is there is a trend that starts to in error statistics. The features are utilizing the fact that the eyes are darker than the cheeks. This feature is present in most human faces and can help detect them.

Round 10

(Type 1) Horizontal Edge Detection

M = 4

N = 1

Position = (8, 16)

Threshold = -22.5

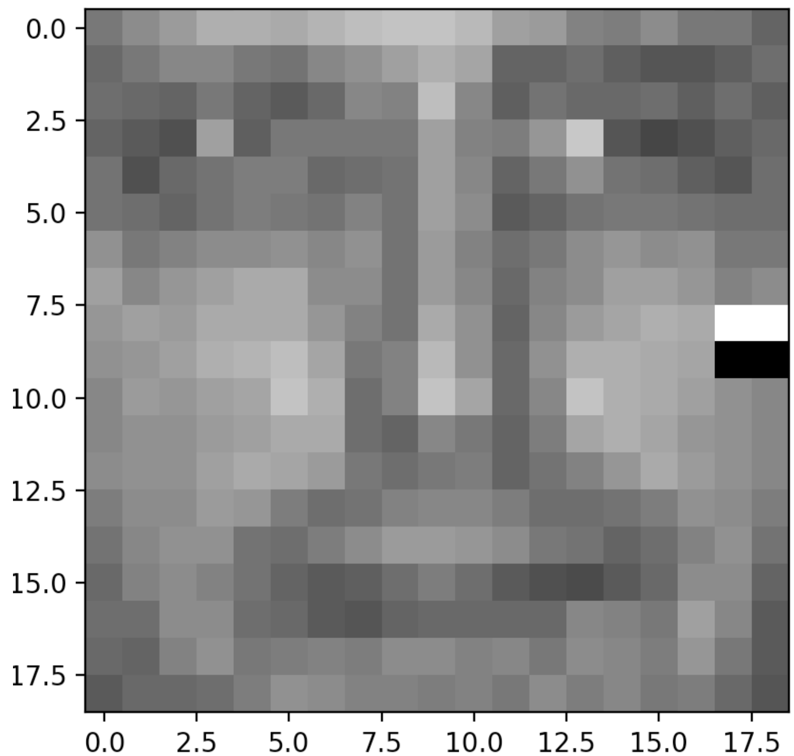

Figure 6(Round 10 features)

In round 10 of the algorithm is saturating in the value of the false negative, while the false-positive error continues to decrease. The features are utilizing the fact that the eyes are darker than the cheeks. This is the same feature type and size of the feature found in round 8. This redundancy may be attributed to size limitation placed on the Haar features.

Ada Boost Medication

Table 2 (Result from different criteria after 5 rounds)

Criterion	Empirical Error	False Positive	False Negative
Empirical Error	0.59384	0.12005	0.47379
(FN) Gama = 0.1	0.44098	0.08964	0.35134
(FP) Gama = 0.9	0.73990	0.05442	0.68547

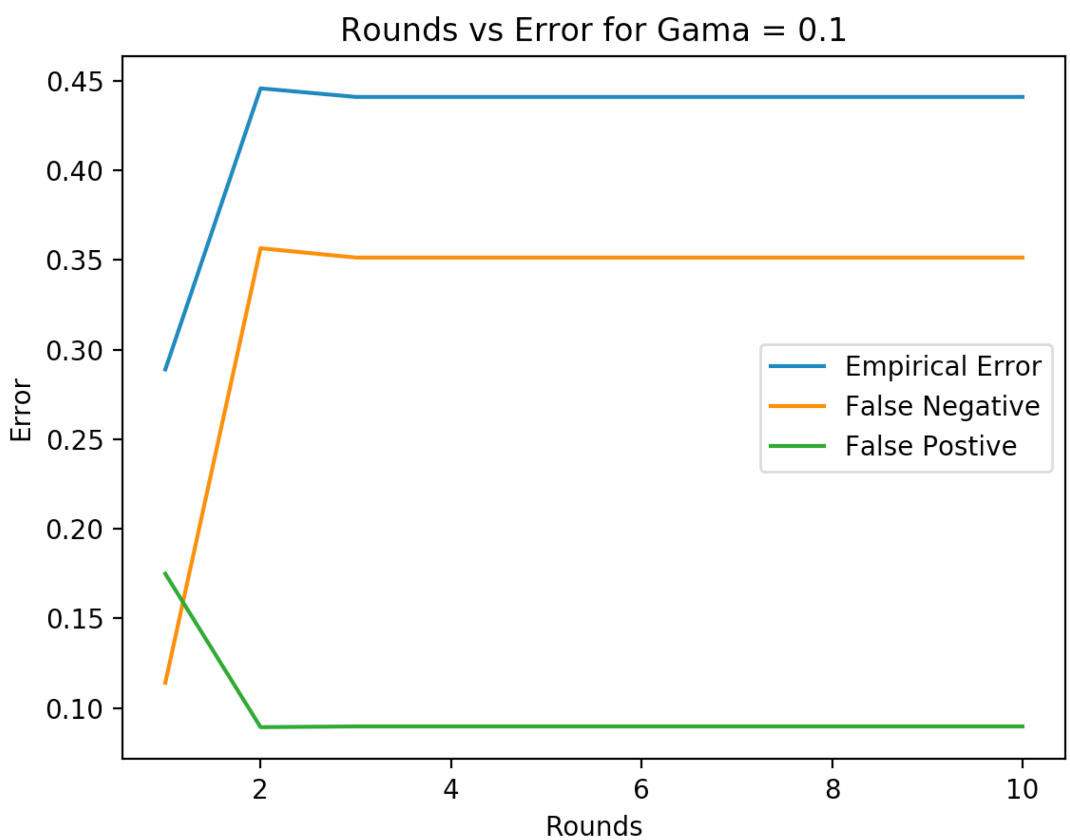

Figure 7(Test errors over 5 rounds of Ada boost with Gama = 0.1)

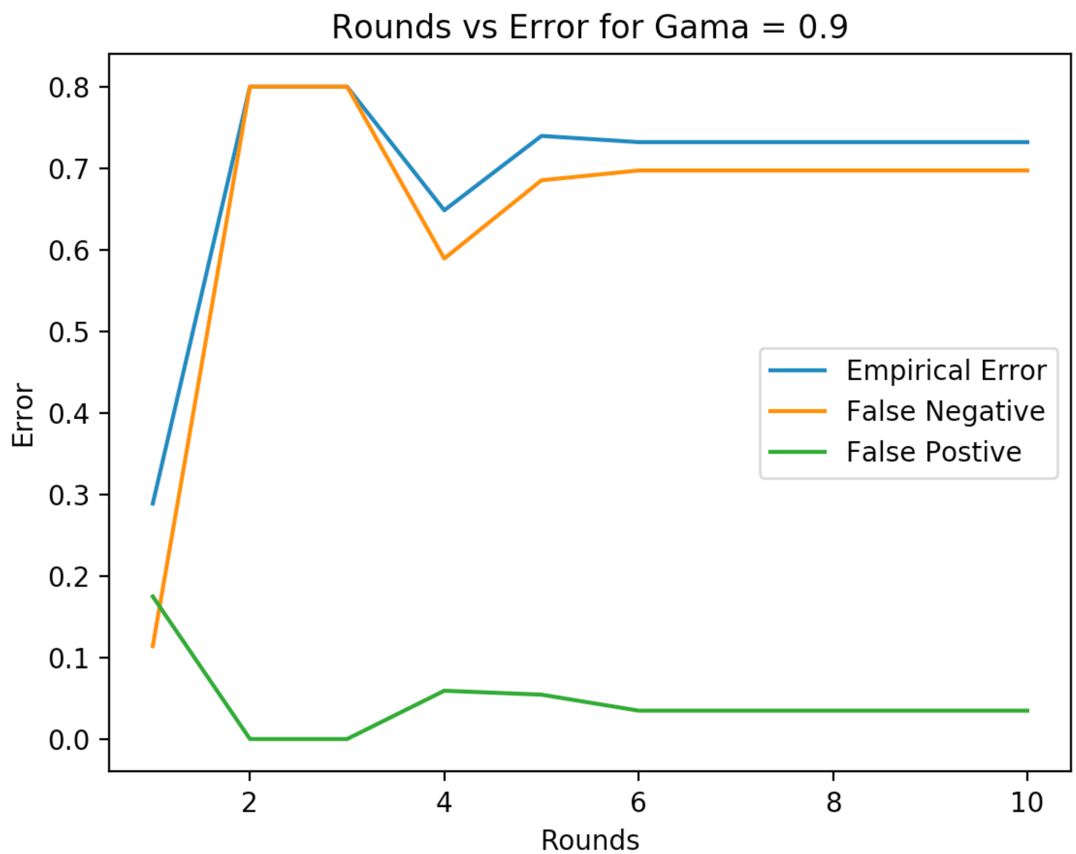

Figure 8(Test errors over 5 rounds of Ada boost with Gama = 0.9)

All of the error were calculated on the testing set of image.

<u>The modification</u>

We modified the ada boost alograitm by weighting the distribution of the faces by a (Gamma) and non- faces (1-Gamma)

$$\gamma \in [0, 1]$$
$$D = (\gamma/size(y == 1) + (1-\gamma)/size(y == -1)) * D_o \beta^{(1-e_i)}$$

Figure 8(Formula used to find the distribution of the new round)

Since the equation weight, the positive and negative data set based on gamma. The value of gamma can be used to change the criteria from false positive to false negative

Conclusion

We were successful in implement all parts of the Ada boost algorithm. I believe that the next step for the project to construct a cascading system, extracting all features from the image and implementing the algorithm real-world images. Another direction of improvement in the project as a whole would be to find a more balanced training dataset, so the disparity between false positive and false negative can be reduces. The results observe were not the standard results, because of feature size was limited to only 8 by 8. The poor features set had a direct the effect on the features selected by the Ada boost.

Reference:

P. Viola and M. Jones, "Rapid object detection using a boosted cascade of simple features," *Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition. CVPR 2001*, Kauai, HI, USA, 2001, pp. I-I.doi: 10.1109/CVPR.2001.990517

https://github.com/Avashist1998/Viola-Jones_Algorithm