Project

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1 Extract Haar Features

A $W \times H$ image contains $(W - m + 1) \times (H - n + 1)$ in total $m \times n$ features.

The total number of Haar Feature is: 63960

There are 17100 type 1 (two vertical) features.

There are 17100 type 2 (two horizontal) features.

There are 10830 type 3 (three horizontal) features.

There are 10830 type 4 (three vertical) features.

There are 8100 type 5 (four) features.

For features with maximum size 8×8,

The total number of Haar Feature is: 26168

There are 7440 type 1 (two vertical) features.

There are 7440 type 2 (two horizontal) features.

There are 3844 type 3 (three horizontal) features.

There are 3844 type 4 (three vertical) features.

There are 3600 type 5 (four) features.

2 Build Your Adaboost Detector

1. 1 round of Adaboost
   The feature: [(0,0),(0,1),(0,2),(1,0),(1,1),(1,2)]
   The threshold: -124, p = -1
   Type: Two horizontal

Position: (0,0)

Width: 2

Height: 1

Threshold: -124

Training Accuracy: 0.8

2. 3 round of Adaboost

   The feature: $[(0,0),(0,1),(0,2),(1,0),(1,1),(1,2)]$, $[(2,13),(5,13),(8,13),(2,18),(5,18),(8,18)]$ $[(7,6),(7,8),(7,10),(14,6),(14,8),(14,10)]$

   The threshold: -124, -346, -151, p = -1

   Top feature: [(2,13),(5,13),(8,13),(2,18),(5,18),(8,18)]

   Type: Two vertical

   Position: (2,13)

   Width: 5

   Height: 6

   Threshold: -346

   Training Accuracy: 0.783

3. 5 rounds of Adaboost

   The feature: $[(0,0),(0,1),(0,2),(1,0),(1,1),(1,2)]$, $[(2,13),(5,13),(8,13),(2,18),(5,18),(8,18)]$ $[(7,6),(7,8),(7,10),(14,6),(14,8),(14,10)]$, $[(10,10),(10,12),(10,14),(11,10),(11,12),(11,14)]$ $[(13,10),(15,10),(17,10),(13,15),(15,15),(17,15)]$

   The threshold: -124, -346, -151, -32, -77, p = -1

   Top feature: [(2,13),(5,13),(8,13),(2,18),(5,18),(8,18)]

   Type: Two vertical

   Position: (2,13)

   Width: 5

   Height: 6

   Threshold: -346

   Training Accuracy: 0.783

4. 10 rounds of Adaboost

   The feature: $[(0,0),(0,1),(0,2),(1,0),(1,1),(1,2)]$

   $[(2,13),(5,13),(8,13),(2,18),(5,18),(8,18)]$

   $[(7,6),(7,8),(7,10),(14,6),(14,8),(14,10)]$

   $[(10,10),(10,12),(10,14),(11,10),(11,12),(11,14)]$

   $[(13,10),(15,10),(17,10),(13,15),(15,15),(17,15)]$

   $[(1,3),(1,6),(1,9),(4,3),(4,6),(4,9),(7,3),(7,6),(7,9)]$

   $[(0,14),(1,14),(2,14),(0,16),(1,16),(2,16)]$

   $[(2,7),(2,8),(2,9),(4,7),(4,8),(4,9)]$

   $[(8,7),(8,8),(8,9),(10,7),(10,8),(10,9),(12,7),(12,8),(12,9)]$

   $[(10,7),(11,7),(12,7),(10,10),(11,10),(12,10)]$

   The threshold: -124, -346, -151, -32, -77, -158, -27, -22, -12, -30, p = -1

   Top feature: [(2,13),(5,13),(8,13),(2,18),(5,18),(8,18)]

   Type: Two Vertical

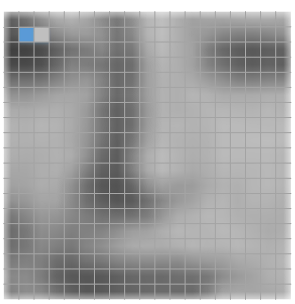
   Position: (2,13)

   Width: 5

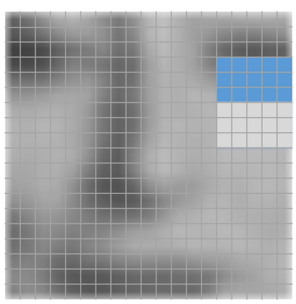
   Height: 6

   Threshold: -346

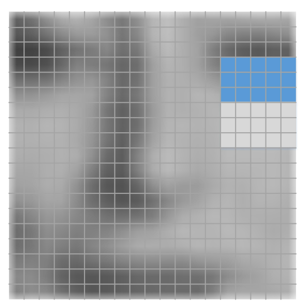
   Training Accuracy: 0.783



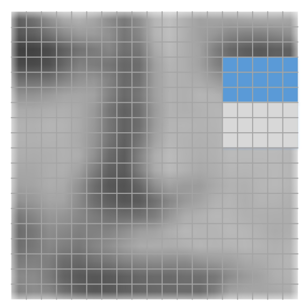
1 round



3 rounds



5 rounds



10 rounds

In training set:

1. Adaboost round 1:

   Total accuracy: 0.8

   False Positive: 0

   False Negative: 0.2

2. Adaboost round 3:

   Total accuracy: 0.836

   False Positive: 0.144

   False Negative: 0.02

3. Adaboost round 5:

   Total accuracy: 0.866

   False Positive: 0.116

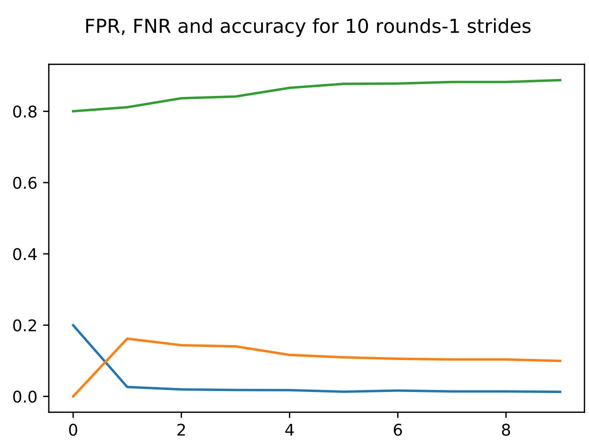
   False Negative: 0.018

4. Adaboost round 10:

   Total accuracy: 0.887

   False Positive: 0.1

   False Negative: 0.013



The accuracy increased and false negative rate and false positive rate is smaller as the rounds grow. This is because the more rounds of adaboost will give a more accurate strong classifier, which will increase its accuracy.

In testing set:

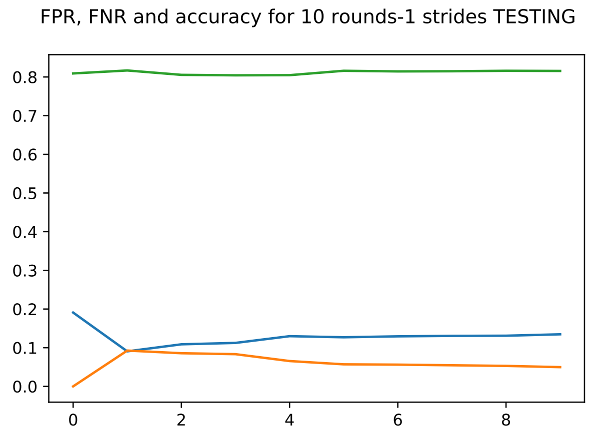
1. Adaboost round 1:
   Total accuracy: 0.809
   False Positive: 0
   False Negative: 0.191

2. Adaboost round 3:
   Total accuracy: 0.805
   False Positive: 0.086
   False Negative: 0.109

3. Adaboost round 5:
   Total accuracy: 0.805
   False Positive: 0.065
   False Negative: 0.130

4. Adaboost round 10:
   Total accuracy: 0.816
   False Positive: 0.049
   False Negative: 0.135

The accuracy increased and false negative rate and false positive rate is smaller as the rounds grow. This is because the more rounds of adaboost will give a more accurate strong classifier, which will increase its accuracy.



3 Adjust the threshold

I changed the error rate calculation during the adaboost. I calculated the empirical error, false positive and false negative as the error rate for each round of adaboost for the three requirements, in order to calculate the weights of each image for the new round.

Criterion	Total Accuracy	False Positive	False Negative
Empirical Error	80.5%	6.5%	13%
False Positive	80.9%	0%	19.1%
False Negative	19.1%	80.9%	0%