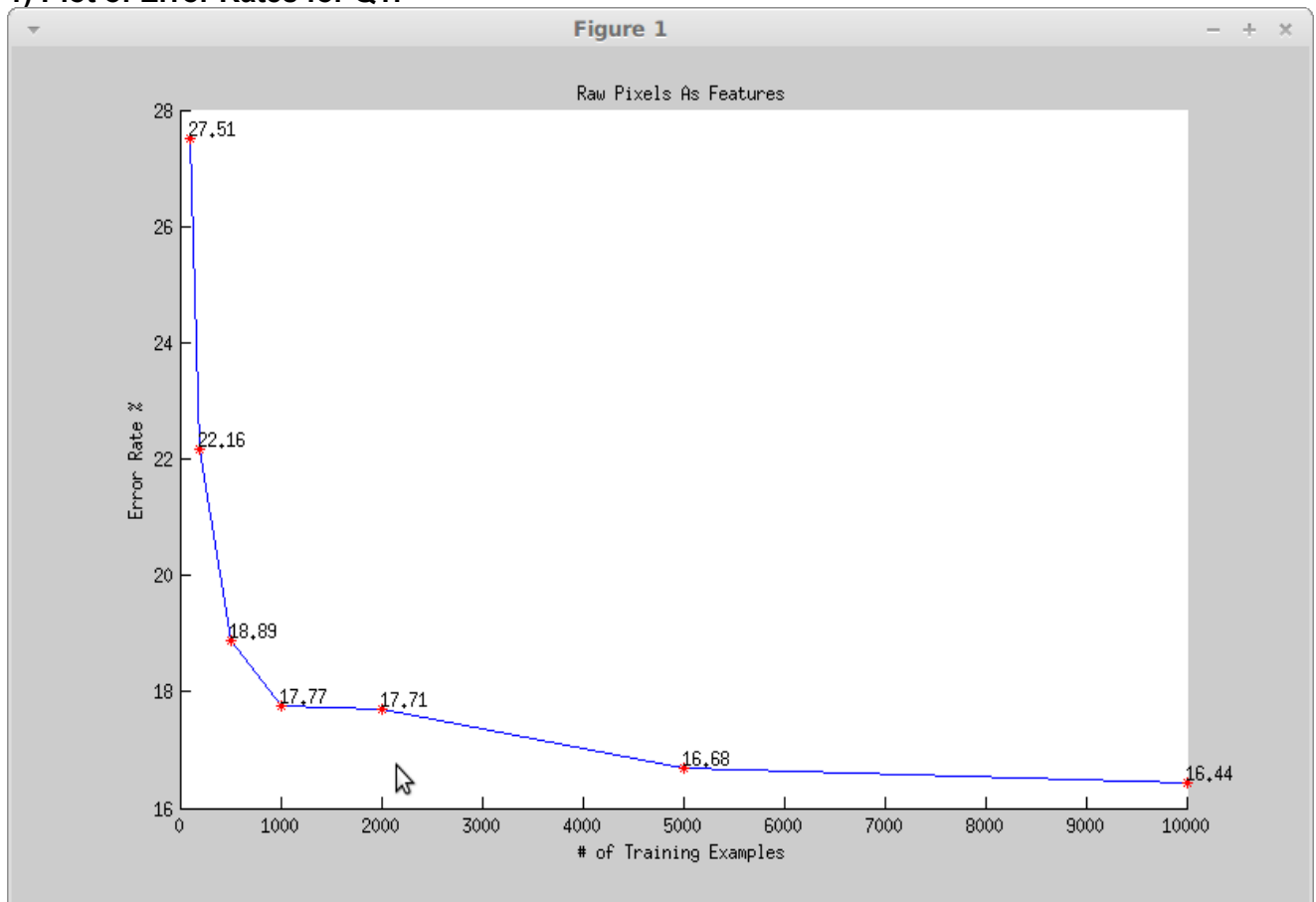


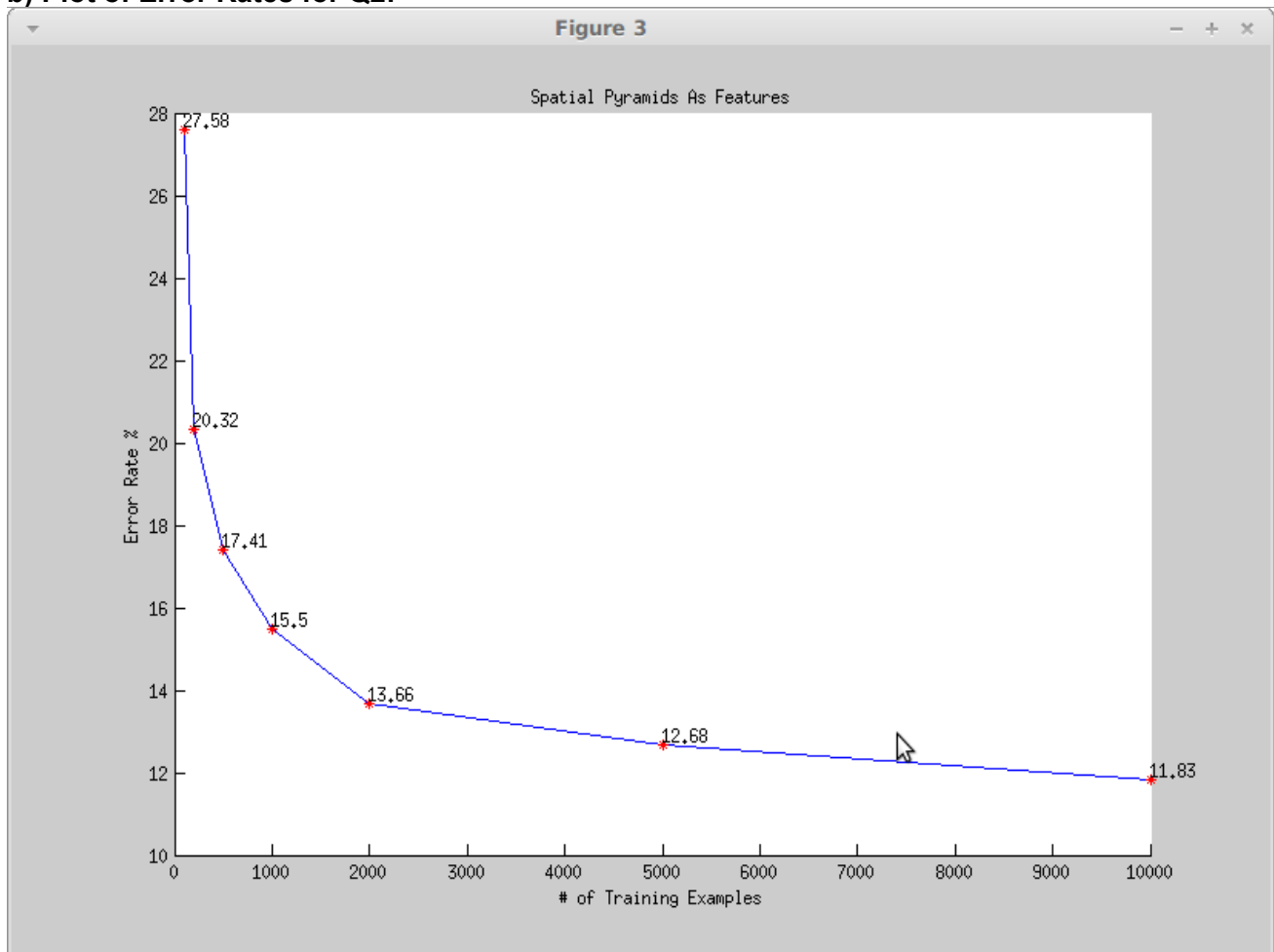
1) Plot of Error Rates for Q1:



2)

a) Adding up these features help over raw pixel values since these features help give us slight invariance over translations, rotation of the training images. This method provides better discriminative power since it provides us with additional information regarding the global spatial information of the image.

b) Plot of Error Rates for Q2:

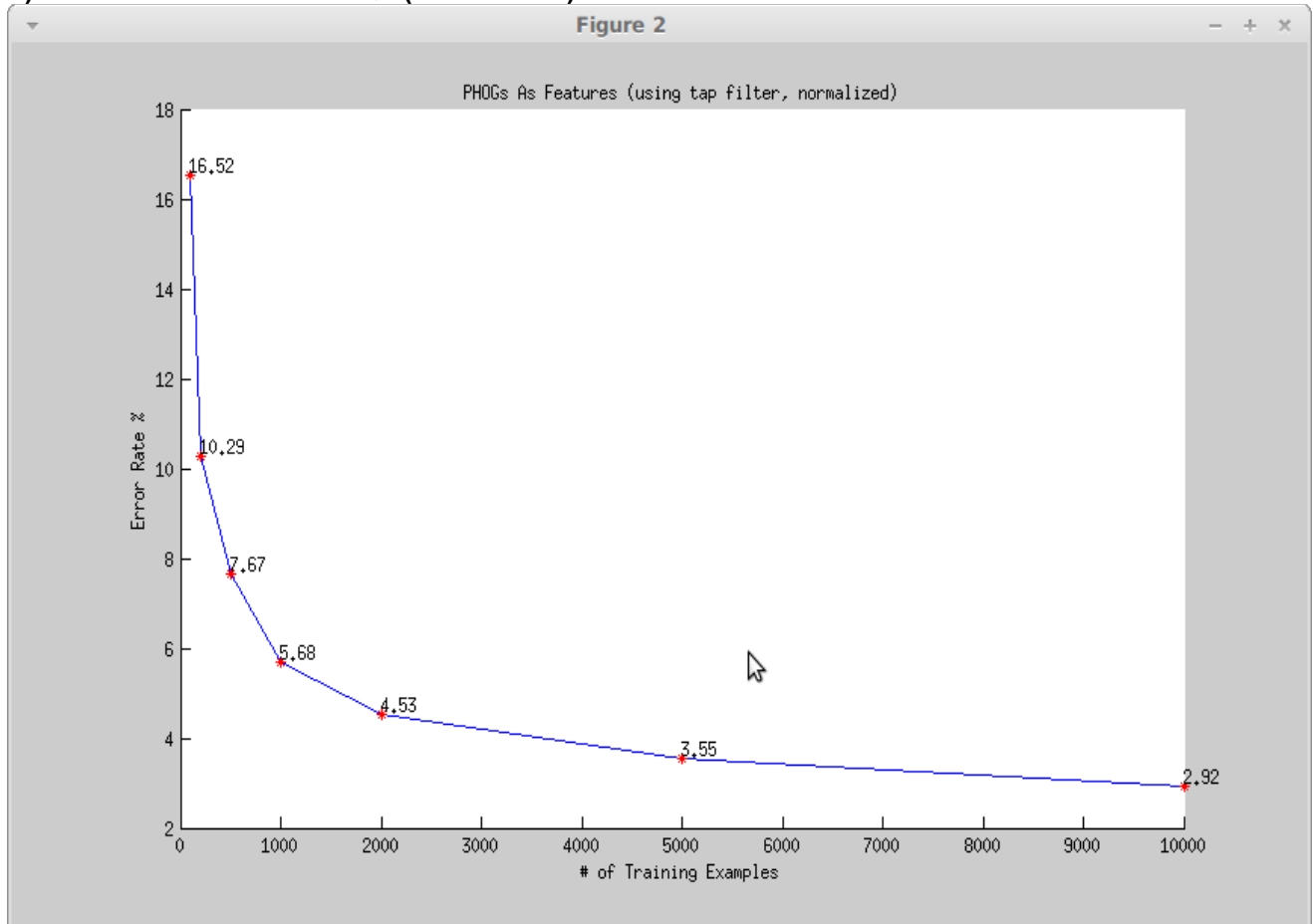


As we can see, this new method gives us a roughly 4 percent reduction in error rates over the Q1 method.

3)

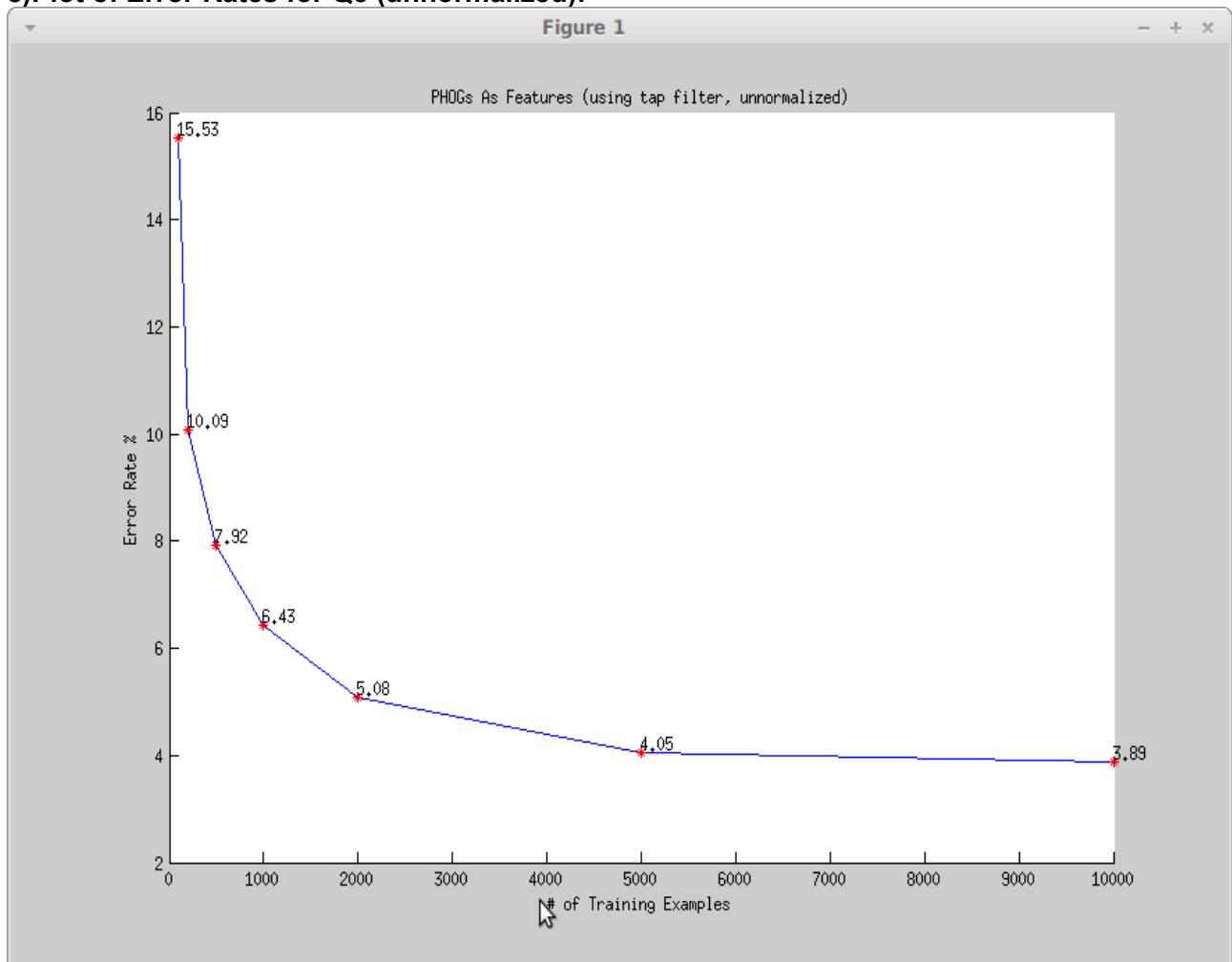
a) Gradient orientation histograms help over summing up pixel intensities since it gives us more invariance regarding shifts and rotation than simple pixel intensities. The reason behind this is because digits are separated from one another based mainly on its shape (which is what gradient orientations capture), and not the intensity of the pixels of the digits.

b) Plot of Error Rates for Q3 (normalized):



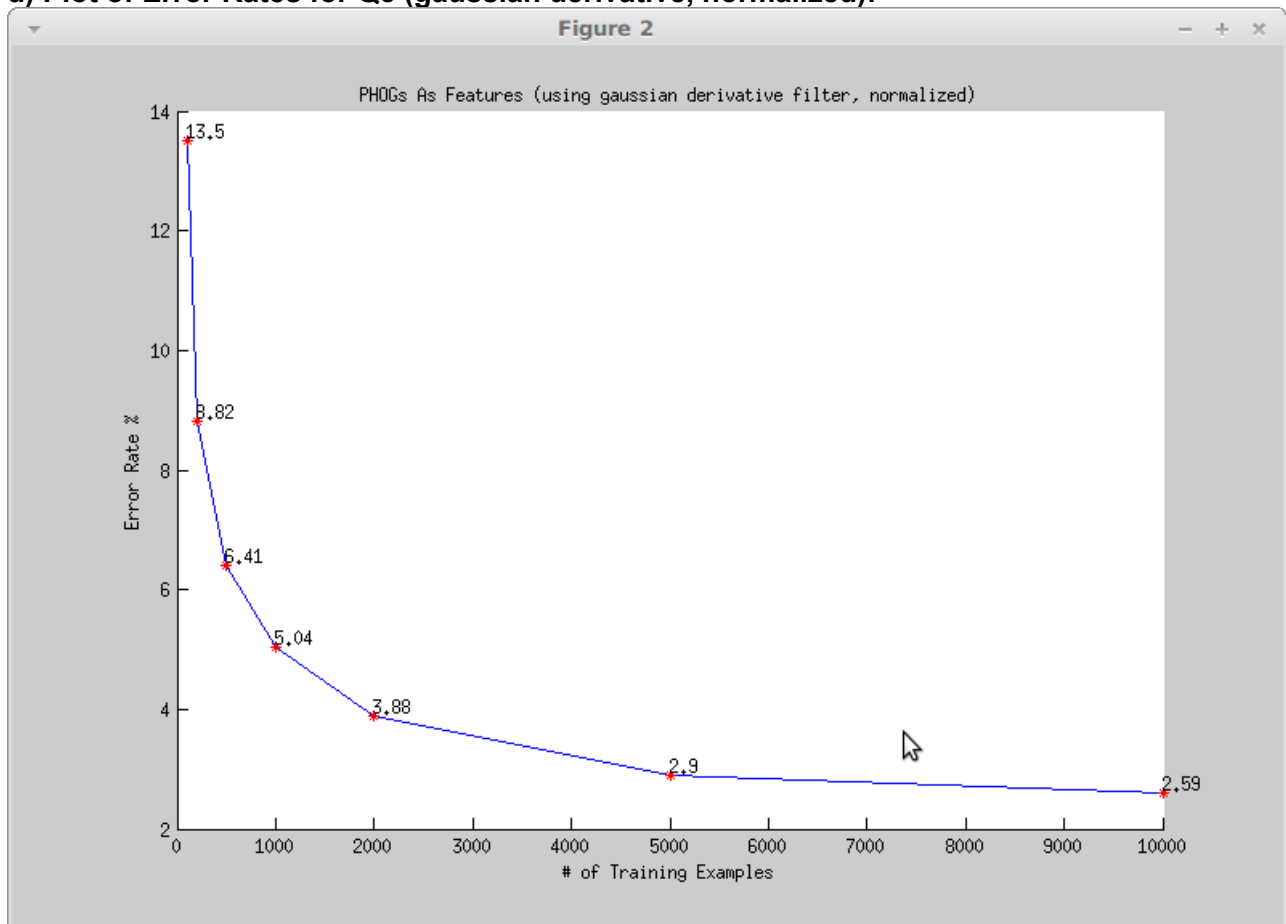
Yes, we get a significant boost in accuracy. The error rate drops from roughly 12 percent (for 10,000 training examples) to less than 3 percent.

**c) Plot of Error Rates for Q3 (unnormalized):**



The performance does drop by 1-2 percent if the histograms are unnormalized. This is probably due to the fact that the  $c=7$  histograms and  $c=4$  histograms have different amount of pixels in them, which creates false skew in the data.

**d) Plot of Error Rates for Q3 (gaussian derivative, normalized):**



The performance is better than part b) by roughly 0.5 percent since the gaussian derivative filter can be seen as a smoother, more sophisticated version of the tap filter.