CENG 483

Introduction to Computer Vision

Spring 2018-2019

Take Home Exam 1

Content Based Image Retrieval

Student Random ID: 15

1 Grayscale Histogram

For greyscale histogram, the following quantization levels have been tested:

- 256 bins : 0.17498 mAP
- 128 bins : 0.17965 mAP
- 64 bins : 0.17679 mAP
- 32 bins : 0.18089 mAP
- 16 bins : 0.18637 mAP

Please note that the results are somewhat similar to each other. We can also see that the best result is the one with the lowest bin number whereas the worst performing is the one with the highest bin number. The reason for this is the differences of illumination and angles for the same scene and the algorithm classifying it differently with respect to its bin number. That is, if we have two of the same scenes but with different light conditions and if we had higher number of bins, we'd have higher distances between the said images. Whereas if we had lower number of bins, we'd have closer distances between the two images since we'd have higher tolerances for the illumination and such. With this explanation in mind, it makes sense that the one with the lower number of bins have slightly higher accuracy since it has the higher tolerance.

2 3D RGB Histogram

For RGB histogram, the following quantization levels have been tested:

- 64 bins : 0.27932 mAP
- 32 bins : 0.35197 mAP
- 16 bins : 0.38524 mAP

- 8 bins : 0.38461 mAP
- 4 bins : 0.32947 mAP

At first glance, we notice that mAP values for RGB histograms are higher than greyscale ones. This is because of the 3-channel information we get from the images. We can also see that the one with 8 bin, a relatively low quantization level is the best performing one. The reason for this is similar to above explanation. As we have lower quantization levels, we have higher tolerance for color changes and therefore light changes. Unlike the first experiment however, as the quantization level goes from 8 to 4, we have lower precision. The reason for this is that we are assigning possibly distinct RGB combinations to the same bin at such low quantization level. Also, as we increase the quantization level, we see a significant drop, especially at 64 bins. Which tells us that effects of having a strict classification and generous classification for bins are more prominent compared to the greyscale case.

3 Gradient Histogram

3.1 Calculation of gradient histogram

For gradients, Prewitt operator has been used. The said operator has the form

$$G_x = 1/3 * \begin{bmatrix} -1 & 0 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}, G_y = 1/3 * \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$$

For calculation of the gradient histogram, firstly, the orientation matrix is calculated. This matrix has the form $\arctan(I_y/I_x)$ where I_y and I_x are the results of the convolution with Prewitt operator. Note that the arctan result is then normalized to be between 0 and $2 * \pi$.

Then, the magnitude matrix of the gradients have been calculated. Again, the said matrix has been calculated via $\sqrt{I_x^2 + I_y^2}$ Then for each orientation bin, the correspondent gradient magnitude is added to that bin and at the end, the results are L-1 normalized for the histogram.

3.2 Visualization

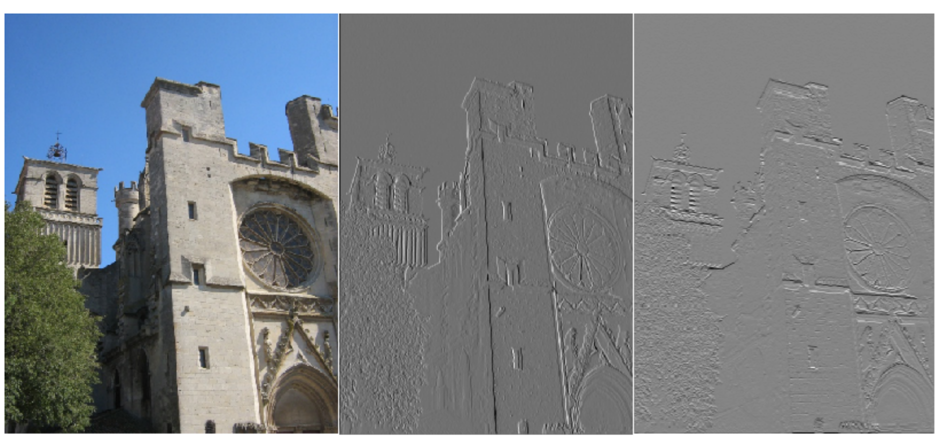

Figure 1: Visualization of the gradients. The second image is the illustration of horizontal gradient, the third is the vertical gradient

3.3 Experimental results

For gradient histogram, the following quantization levels have been tested:

- 360 bins : 0.28940 mAP
- 90 bins : 0.29297 mAP
- 45 bins : 0.27062 mAP

3.4 Comments and Explanations

Between 45 and 90 bins, we see an increase in precision because the gradients are usually invariant to lighting conditions. I.e, the edges themselves doesn't change with different lighting conditions. So as we increase our sampling rate, we expect to have a better precision for identifying similar pictures. However, we notice that upon increasing the bin size to 360, we see a slight drop in precision. Increasing the bin number means smaller orientation differences in the picture gets mapped into a different bin. Since we lose the locality in the picture with grid level 1 histograms, it's important to have neither a strict nor generous number of quantization.

4 Grid Based Feature Extraction

4.1 Level 1

- grayscale histogram: 0.18637 mAP
- 3d rgb histogram: 0.38524 mAP
- gradient histogram: 0.29297 mAP

4.2 Level 2

- grayscale histogram: 0.26965 mAP
- 3d rgb histogram: 0.38763 mAP
- gradient histogram: 0.34957 mAP

4.3 Level 3

- grayscale histogram: 0.28289 mAP
- 3d rgb histogram: 0.32020 mAP
- gradient histogram: 0.35983 mAP

4.4 Questions

- What do you think cause the difference between the results?

  As we increase the grid level, we start to acquire the location information we lost. Hence, we see an increase of precision going from level 1 to level 2. However, since RGB configuration heavily relied on level 1 grid data, we see a decrease of precision at level 3. Also, as we acquire more locality information, we may decrease the bin size for higher precision. For example, in our tests RGB histogram with bin size of 8 at level 2 gave us 0.40732 mAP.

- How did you combine the histograms in level 2 and 3? What would you think the difference between to simply sum them and to concatenate them?

  For each sub image, I've created a histogram of their own. That is, at grid level 3 we have 16 histograms that each represent their own region. If we were to simply sum the results, we would have lost the locality and the result would be same as that of grid level 1(ignoring the loss from floating point arithmetic)

5 Your Best Configuration

- You may try different combinations including changing parameters above and even combining different methods. Simply give your best mAP for the validation set:

  Using combinations of above configurations, **0.46482 mAP** have been reached.

- Explain your setup for this best mAP. How can we reproduce your result using your code?

  The setup consists of the following combinations of configurations:

  - RGB Histogram;Bin #:8, Grid level:2, Weight:21
  - Greyscale Histogram;Bin #:16, Grid level:3, Weight:3
  - Gradient Histogram;Bin #:90, Grid level:3, Weight:58

  While combining the differences of histograms, I've used the said weights for the total difference calculation. After RGB, greyscale and gradient histograms are compared, the differences are multiplied with above weights and then summed together.(i.e 21*rgbDiff + 3*gsDiff + 58*gradDiff) Note that bin size of 8 for RGB performed better at level 3.

  For the recreation of the above results, run the program as **python3 hw.py best-configuration**. The result is saved as **result.out**

- Give some visual ranking results:

Figure 2: A visual ranking. Left image is the query image whereas the right ones are the top 3 results

- Explain mean average precision in your own words:

  mAP: The average precision(AP) is the average 'true positive' hit rate for a query among all positive results which favors the higher ranks in a set sorted by a distance metric. Therefore the lower ranked results which are true positives contribute less to this rate. Mean average precision(mAP) on the other hand is the average of APs for many queries which gives us an overall performance for a set of queries.

6 Additional Comments and References

When used Chi-Squared distance instead of Euclidean distance during the histogram comparison, it's possible to achieve **0.60536 mAP**. You can recreate the results via **python3 hw3.py config-chisqr**