CS419 Homework 2

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Question 4

a) **Opening Operation Suitability:** The objects of interest are sometimes brighter and sometimes darker with respect to their surroundings. Is using opening going to be sufficient?

Answer: Within the context of our question, the implementation of the opening operation appears as the strategy of choice. The examination that is in my notebook, notably in Section 5a, supports this conclusion. A careful examination of the tophat method was done in pursuit of image processing, with the primary goal of minimizing the impact of divergent sections exhibiting fluctuations in brightness relative to their surroundings.The idea behind this investigation was based on the hope that, following the application of the tophat operation, the images would go through brightness harmonization, establishing the base for later granulometry processes, including the opening operation. However, I concluded that the resulting images, while achieving a degree of brightness uniformity, would be unsatisfactory for the granulometry procedures required for the subtle separation of objects of varying sizes within our photos. Because the resulting images are too uniform and non of the objects with different sizes are not dedectable. As a result, the opening procedure would be sufficent in our question.

b) **Structuring Element Sizes:** What shape/range of sizes of structuring elements should you use?

Answer: I conducted an analysis in order to answer the question of the ideal shape and size range of structural elements, it is provided in Section 4b of the notebook. The examination attempted to determine the effect of different structuring element sizes on the results of granulometry operations. Surprisingly, the analysis indicated that changes in the sizes of structuring elements, whether slight or significant, had no effect on the outcomes. This discovery was supported by the execution of two granulometry processes with structural elements ranging in size from 20 to 120.Surprisingly, despite the variation in structure element sizes, the outcomes remained same. So in our case the size of the structral element can does not effect the outcome. The circular kernel was carefully selected as the shape of the structuring element. The inherent qualities of the objects under examination, which have a largely circular shape due to their rock-like shapes, influenced this conclusion. The circular kernel is designed to identify items of varied sizes, which corresponds to the geological nature of the objects in question. As a result, the use of a circular structural element appears as a strategic and practical solution, improving the accuracy of the granulometry procedures in discriminating various sizes of rocks within the photographs.

c) **Opening/Closing vs. Opening/Closing by Reconstruction:** Should you use openings/closings or openings/closings by reconstruction?

Answer: In the context of image processing approaches for our specific goals, the right choice is to choose opening and closing processes over alternatives using reconstruction opening and closing. This conclusion is based on the unique characteristics of these procedures and their effects on the image structure. Opening and closing procedures act as effective filters, removing elements smaller than the structuring element and offering a way for simplifying the image while preserving crucial structural aspects. By reducing unwanted noise and fine-scale features, these techniques improve object discrimination and characterization.Opening and closing by reconstruction, on the other hand, takes a more subtle approach, attempting to preserve important aspects while removing minor structures. This approach is especially useful in situations where important image properties must be preserved. However, the fundamental goal of our granulometry operations is the deliberate elimination of tiny characteristics to aid in the identification and detection of objects of various forms. As a result, using opening and closing operations corresponds with our main goal of efficiently reducing picture data by removing unnecessary information and improving subsequent granulometry analysis.

d) **Granulometry Comparison:** If you calculate the granulometry of an unlabeled image, how are you supposed to compare the resulting numerical series against the granulometry of a labeled image? Should you rely on the Euclidean distance? Or their Manhattan distance? Or Chebyshev distance? Or something entirely different?

Answer: As pointed out in Section 4d of the notebook, I did a systematic evaluation of various distance metrics, including Manhattan, Euclidean, and Chebyshev distances. The goal was to determine how these parameters affected the granulometry process and how effective they were in classifying unlabeled photos. Surprisingly, the results indicated great consistency across all distances studied—Manhattan, Euclidean, and Chebyshev. In the granulometry method, each distance metric consistently produced consistent results, correctly concluding and classifying unlabeled photos . This striking consistency means that, for the precise aims at hand, the choice of distance metric appears to be insignificant, as all evaluated metrics performed same in appropriately categorizing the photographs. . As a result, we are able to use any of the metrics under consideration interchangeably, as each is as effective in obtaining the desired classification accuracy for unlabeled photos.

Question 5

a) **Filtering Performance:** To determine which filter performs best, I calculated the Mean Squared Error (MSE) values for four filters: Lexicographical, Bitmix, Norm, and Marginal. The MSE values are presented in Table 1.

Filter	Avrage MSE Value
Lexicographical	22.2210
Bitmix	21.7364
Norm	37.4334
Marginal	18.8689

Table 1: MSE Values for Different Filters

As we can see by the average MSE results the best method that filters the image with least amount of MSE is Marginal (scalar) processing. This table and analysis can be seen in my notebook at section 5b.

b) **Performance Dependency on Image:** To further analyze the performance dependency on the image, I conducted experiments with 10 different images. For each filter, Table 2 shows the MSE values for each image.

Image	Lexicographical	Bitmix	Norm	Marginal
Image 1	12.4420	12.9457	23.8791	10.1926
Image 2	12.8249	13.0695	26.1050	11.6826
Image 3	19.5524	18.7703	35.1774	16.5420
Image 4	23.2605	23.3473	34.2930	21.3718
Image 5	19.5893	17.6400	35.9428	12.8701
Image 6	10.5675	10.0227	24.7784	5.9398
Image 7	18.1369	17.6578	31.8939	16.0121
Image 8	56.8151	56.1593	76.3069	53.0739
Image 9	37.0199	35.8373	58.1792	30.5835
Image 10	12.0012	11.9143	27.7781	10.4204

Table 2: MSE Values for Different Images and Filters

As seen in Table 2, each filter exhibits different behavior for each image, indicating that the performance of the filter is dependent on the characteristics of the specific image.But even the performance of each filter changes with the image still the best method that filters the images best is Marginal strategy. This table and analysis can be seen in my notebook at section 5a.

c) **Effect of Noise Level/Correlation:** The correlation of noise was varied to assess its impact on filtering performance. The average MSE results for different noise probabilities are presented in Table 3.

The noise level has a substantial impact on the performance of the filters, as evidenced by the average MSE results for different noise probabilities in Table 3. But again the best method that filters the images best is Marginal strategy even

Noise Probability	Lexicographical MSE	Bitmix MSE	Norm MSE	Marginal MSE
0.01	21.9256	21.4194	37.2237	18.5800
0.02	22.2286	21.7625	37.4564	18.8975
0.03	22.4938	22.0819	37.7259	19.1645
0.04	22.7649	22.4183	38.0046	19.4863
0.05	23.0394	22.6929	38.3218	19.7400

Table 3: Average MSE Values for Different Noise Probabilities and Filters

with different levels of noise.This table and analysis can be seen in my notebook at section 5c.

d) **Effect of Filter Size:** I analyzed the effect of kernel size on performance of filtering strategies on image filtering. The correlation of kernel size was varied to assess its impact on filtering performance. The average MSE results for different kernel sizes are presented in Table 4.

Kernel Size	Lexicographical MSE	Bitmix MSE	Norm MSE	Marginal MSE
3	22.2315	21.7557	37.4571	18.8891
5	33.4067	32.8009	49.7911	29.1025
7	40.1465	39.5219	56.8573	35.4498

Table 4: Average MSE Values for Different Kernel Sizes and Filters

The kernel size has a substantial impact on the performance of the filters, as evidenced by the average MSE results for different kernel sizes in Table 4. But again the best method that filters the images best is Marginal strategy even with different kernel sizes.This table and analysis can be seen in my notebook at section 5d.

e) **Effect of Color Space:** To determine the effect of color spaces on performance of the filtering strategies on image filtering, I calculated the Mean Squared Error (MSE) values for four filters: Lexicographical, Bitmix, Norm, and Marginal on color space LAB. The MSE values are presented in Table 1.

Filter	Avrage MSE(RGB)	Avrage MSE(LAB)
Lexicographical	22.2210	9.6324
Bitmix	21.7364	12.6292
Norm	37.4334	17.9375
Marginal	18.8689	7.6141

Table 5: MSE Values for Different Filters

As can be seen by the average MSE values at the Table 5 effect of the color space is evident when the avrage MSE values on the RGB color space is compared to avrage MSE values in LAB color space.The performance of the filtering strategies on image filtering varies when there is a change of color space.But again the best method that filters the images best is Marginal strategy even in a diffrent color space.This table and analysis can be seen in my notebook at section 5e.