CIS 663 Biometrics

Assignment 2

# **This assignment is due by the day of week 6 live session. If you make any assumptions, clearly state them in your answer.**

1. The following represents a 10 x 10-pixel grayscale. 0 represents black and 255 represents white.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 |
| 0 | 0 | 3 | 3 | 3 | 3 | 3 | 2 | 1 | 1 |
| 0 | 0 | 3 | 3 | 4 | 4 | 4 | 4 | 4 | 4 |
| 0 | 0 | 3 | 3 | 3 | 3 | 4 | 4 | 4 | 4 |
| 0 | 0 | 0 | 1 | 1 | 3 | 4 | 4 | 4 | 4 |
| 0 | 0 | 0 | 0 | 0 | 4 | 4 | 4 | 1 | 0 |
| 5 | 5 | 0 | 0 | 0 | 4 | 4 | 4 | 0 | 0 |
| 5 | 5 | 0 | 0 | 0 | 4 | 4 | 4 | 0 | 0 |
| 5 | 5 | 0 | 0 | 0 | 0 | 5 | 5 | 0 | 0 |
| 5 | 5 | 0 | 0 | 0 | 0 | 5 | 5 | 0 | 0 |

* 1. Convert the image to an integral image. (10pt)

Converted to Integral Image

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 2 | 3 |
| 0 | 0 | 3 | 6 | 9 | 12 | 15 | 18 | 20 | 22 |
| 0 | 0 | 6 | 12 | 19 | 26 | 33 | 40 | 46 | 52 |
| 0 | 0 | 9 | 18 | 28 | 38 | 49 | 60 | 70 | 80 |
| 0 | 0 | 9 | 19 | 30 | 43 | 58 | 73 | 87 | 101 |
| 0 | 0 | 9 | 19 | 30 | 47 | 66 | 85 | 100 | 114 |
| 5 | 10 | 19 | 29 | 40 | 61 | 84 | 107 | 122 | 136 |
| 10 | 20 | 29 | 39 | 50 | 75 | 102 | 129 | 144 | 158 |
| 15 | 30 | 39 | 49 | 60 | 85 | 117 | 149 | 164 | 178 |
| 20 | 40 | 49 | 59 | 70 | 95 | 132 | 169 | 184 | 198 |

* 1. Using the integral image, compute the sum of area from (2,2) to (5,7), shaded red above. Show your steps. (10pt)

Sum=*I*(*D*)−*I*(*B*)−*I*(*C*)+*I*(*A*)

Where A*A*, B*B*, C*C*, and D*D* are the corners of the rectangle:

* A is the top-left corner.
* B is the top-right corner.
* C is the bottom-left corner.
* D is the bottom-right corner.
* *A*=(2,2)=6
* B=(2,7)=46
* C=(5,2)=14
* D=(5,7)=75

**So, the sum is:**

Sum = 75 − 46 − 14 + 6 = 15 + 6 = **21**

1. Using the grayscale image from Question 1, apply the following Haar filter to all positions that are feasible. (20pts)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  |  |  |  |  |  |
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|  |  |  |  |  |  |

* **Black Regions**: These regions represent areas where one expects lower intensity or pixel values. In the context of edge detection, for example, this might correspond to the darker side of an edge.
* **White Regions**: Conversely, these regions represent areas where one expects higher intensity or pixel values. This might correspond to the lighter side of an edge.

The subtraction of the sum of pixels in the black region from the sum of pixels in the white region provides a measure of contrast between these areas. The greater the difference, the more pronounced the pattern represented by the Haar-like feature is in the image.

There is code attached that applies the Haar Filter to the image, the output is:

[-9, -24, -29, -19, -19]

[-23, -37, -32, -13, -14]

[-37, -47, -31, -6, -7]

[-45, -53, -35, 1, 11]

[-55, -59, -37, 8, 27]

1. In Viola-Jones face detection algorithm, explain what cascading is and why it is important. (20pt)

The Viola-Jones face detection algorithm is a pioneering method for real-time face detection that employs a machine learning approach using a cascade of classifiers. In this context, "cascading" refers to the specific structure and process used to quickly discard non-face regions, allowing the algorithm to focus on promising areas that may contain a face.

**About Cascading:**

1. **Structure of the Cascade**: The cascade is made up of several stages, each containing a simple classifier. These classifiers are trained to recognize faces, but each stage is only designed to recognize a part of the complexity of a face.
2. **Processing Stages**: An image region is processed through the stages of the cascade sequentially. At each stage, the classifier determines whether the region may contain a face.
3. **Quick Rejection**: If a stage in the cascade classifies the region as a non-face, the processing of that region is stopped, and it is immediately discarded as a non-face region. The cascade is designed so that the early stages are very simple and are likely to reject many non-face regions.
4. **Continued Processing**: If a region passes a stage, it continues to the next stage in the cascade. As the region progresses through the cascade, the classifiers become more complex and are more accurate but computationally more expensive.
5. **Final Decision**: If a region passes all the stages of the cascade, it is classified as a face.

**Importance of Cascading:**

1. **Speed**: By rejecting non-face regions quickly in the early stages, the algorithm avoids wasting computational resources on them. This allows the Viola-Jones method to achieve real-time performance, even though later stages of the cascade may be computationally intensive.
2. **Scalability**: The cascade structure is flexible and can be adapted to different performance needs. By adjusting the number of stages and the complexity of the classifiers, the cascade can be tuned for different accuracy and speed trade-offs.
3. **Focus on Promising Regions**: By progressively filtering out non-face regions and only spending computational resources on promising areas, the algorithm is more effective at accurately detecting faces.
4. **Reduction of False Positives**: By employing increasingly complex classifiers at each stage, the algorithm reduces the chance of false positives. This layered approach allows for a more refined and accurate classification.

In summary, cascading in the Viola-Jones face detection algorithm is a multi-stage process designed to quickly and efficiently identify regions that may contain faces, concentrating computational efforts on promising regions, and thereby enabling real-time performance. Its ability to reject non-face regions rapidly is central to its effectiveness and efficiency, making it a significant advancement in the field of face detection.

1. What is Principle Component Analysis and how does it relate to face recognition? (20pts)

Principal Component Analysis (PCA) is a statistical method that involves transforming data into a new coordinate system where the data's variance is maximized along new axes. Essentially, it reduces the dimensionality of the data by finding the "principal components" that capture the most information about the underlying structure of the data.

**Principal Component Analysis (PCA):**

1. **Standardization**: Often, the first step in PCA is to standardize the data, so that each feature has a mean of zero and a standard deviation of one.
2. **Covariance Matrix**: Next, the covariance matrix of the standardized data is computed. This matrix describes how the different features vary together.
3. **Eigenvalue Decomposition**: The covariance matrix is then decomposed into its eigenvectors and eigenvalues. The eigenvectors represent the directions in which the data varies the most, and the eigenvalues tell you how much variation there is in each direction.
4. **Select Principal Components**: The eigenvectors are ranked by their corresponding eigenvalues, and the top eigenvectors are selected. These top eigenvectors define the new coordinate system where the data's variance is maximized.
5. **Transform Data**: Finally, the original data is projected onto the new coordinate system defined by the top eigenvectors. This reduces the dimensionality of the data while retaining as much of the original variability as possible.

**Relation to Face Recognition:**

PCA is often used in face recognition as a technique to reduce the dimensionality of the data and to remove noise or irrelevant information.

1. **Feature Reduction**: Images of faces can contain thousands of pixels, leading to high dimensionality. PCA can be used to reduce this dimensionality by projecting the images into a space defined by the principal components, which capture the most important variations between faces.
2. **Eigenfaces**: In the context of face recognition, the principal components are sometimes referred to as "eigenfaces." These eigenfaces represent the main patterns of variation within the set of face images. A given face can be represented as a combination of these eigenfaces, plus a mean face.
3. **Comparison and Classification**: In a reduced-dimensional space, faces can be compared more easily, and similarities and differences between them can be quantified. This makes it possible to recognize an individual's face by comparing it to a database of known faces.
4. **Noise Reduction**: PCA can also help to remove noise and irrelevant information from the face images, potentially improving the accuracy of face recognition.
5. **Computational Efficiency**: By reducing the dimensionality of the data, PCA can make subsequent computations more efficient, which is an important consideration for real-time face recognition systems.

In summary, PCA is a vital tool in face recognition, providing a method to reduce dimensionality, remove noise, and create a more manageable and informative representation of face images.