# Project Report
Engineering Modelling Lab

## Face Recognition Using LBP and Haar Cascade in MATLAB

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## Introduction:

This project creates a facial recognition system that can recognise an individual in a group photo by comparing it to a reference image. The system, which is implemented with MATLAB, does face detection, feature extraction, and precise matching based on texture and geometry utilising the Computer Vision Toolbox and Image Processing Toolbox.

## Scope:

There are numerous real-world uses for the facial recognition system in a variety of fields. It improves security and convenience by authenticating people and immediately unlocking the door upon successful recognition in smart door lock systems. CCTV surveillance systems may identify or follow people in real time by comparing faces from live camera feeds to a database. By using facial recognition to identify and log pupils or employees, it enables automated attendance systems for business or educational settings, doing away with the need for manual tracking. The method can also be used for driver identification in the automobile industry, and will allow only authorised people to enter the car.

## Software Tools:

- MATLAB
- Computer Vision Toolbox
- Image Processing Toolbox

### Process Flow:

The face recognition system follows a structured and systematic process flow, beginning with image input. In this initial phase, the system loads two distinct images: the reference image and the group image. The reference image typically contains a clear, frontal face of an individual, often sourced from passport photos, ID cards, or other official documents. This image serves as the baseline or template against which the system will compare other faces. It is crucial that the reference image be well-lit, with minimal occlusions or distortions, to ensure the highest accuracy in feature extraction and comparison.

The second image, the group image, contains multiple faces, which may belong to different individuals. This image could be captured in various settings, such as crowds, meetings, or public events, where multiple faces need to be detected and analyzed simultaneously. The challenge in this phase is detecting and isolating the faces from a potentially complex background, which may include several people, varying lighting conditions, and different facial orientations. The system must efficiently identify the locations of the faces in the group image to ensure that the correct features are extracted for further analysis.

Once both images are loaded, the system begins the face detection process, where it automatically identifies potential facial regions in both the reference and group images. These regions are then isolated for feature extraction, ensuring that only relevant facial data is used in the subsequent comparison and recognition phases. This initial step of image input and face detection is crucial, as it establishes the foundation for the system's accuracy and effectiveness. The precision of these early stages directly impacts the quality of feature matching, recognition, and the system’s overall performance in real-world applications.

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## Grey Scale Conversion:

These images, typically in jpg format, are next subjected to grayscale conversion to reduce computational complexity, eliminate color-related noise, and enhance the accuracy of face detection and feature extraction.

## Haar Cascade classifier:

After the preprocessing step, the system proceeds to the face detection module, a very important step in finding and isolating the facial regions from the group image as well as from the reference image. Here, the system utilizes the Haar Cascade classifier, a machine learning-based object detection algorithm that is quick and widely adopted, being optimally trained for the detection of human faces from direct visual cues.

The Haar Cascade classifier functions on the detection of pixel intensity change patterns, particularly those for facial features and contrast such as darker patches near the eyes, eyebrows, and mouth with respect to lighter patches like the forehead and cheeks. These are captured in terms of Haar-like features, which are just groups of neighboring rectangular patches of different scales and positions. All features calculate the pixel intensity difference over such areas to detect structural features typical of human faces.

For strong detection rates and generalization, the classifier is trained beforehand with thousands of positive (face) and negative (non-face) training samples. Following intensive training, it can uniquely detect frontal human faces under varying lighting conditions and backgrounds and have scarcely any false positives.

If it is applied to the reference image, the classifier will be able to identify more than one face-like region in the case of an image that is complex in the background, has deep shadows, or is noisy. To prevent this, the system uses a size-based bounding box selection technique. From all the faces identified, the system chooses and returns the largest bounding rectangle assuming that the reference face (closest to the picture) is the largest. This prevents incorrectly selecting objects in the background or background regions with face-like patterns.

After the detection of the face, it gets resized and cropped into a constant size of 100×100 pixels. Image scale and maintaining consistency in the resolution is facilitated through resizing so that during comparison and matching at the feature extraction and matching levels, accuracy as well as an unbiased comparison could be ensured. Having a consistent image size renders the calculation of the feature vector simpler and keeps the system processes with low-dimensional simplicity.

Similarly, in the group photo that may have more than one individual—the Haar Cascade face detector is used to detect all frontal faces. The face is cropped and resized with the same procedure being applied to the reference face to make things uniform in the dataset. The detected faces are then passed to the feature extraction module to process.

Overall, the Haar Cascade-based face detection algorithm provides a fast and efficient way of isolating faces from the real world, making it suitable for applications where speed and resource limits are critical factors.

## Local Binary Pattern (LBP):

Having detected face regions using the Haar Cascade classifier, the second critical step of the face recognition pipeline is feature extraction. Here, raw pixel data are encoded into a more compact and informative representation that enables effective matching of faces. The system achieves this with the Local Binary Pattern (LBP) technique—a robust and efficient texture descriptor widely applied in image processing and pattern recognition problems.

LBP compares neighboring pixels surrounding the center pixel of a window with the center pixel itself for each center pixel in the window for any given input image, typically in a 3×3 window. If the neighboring pixel value equals or surpasses the center pixel value, then a binary value of 1 is assigned to the neighboring pixel; otherwise, it is assigned 0. Scanning off the binary values in a clockwise or counterclockwise direction produces an 8-bit binary number to map the local pattern of texture. This binary value is then converted into a decimal value, which is the LBP code of this center pixel.

Through performing this operation in a step-by-step fashion to the whole face region, the system constructs a feature map of LBP descriptors that are able to capture the micro-patterns and variations in facial texture. The patterns are indicative of such facial features as edges, spots, and planes that are immune to lighting changes as well as moderate facial expressions—placing LBP in the most suitable position for facial recognition.

Once the transformation of LBP is completed, a histogram of the LBP values is calculated to describe the global facial texture in a concise form. The histogram is the face's feature vector and contains significant discriminatory information that is used to compare and recognize subjects.

LBP features are extracted for the reference face (the stored known person in the system database) and for each face detected in the group image or live input stream. These features are stored in a structured manner and then used during matching, where similarity measures such as Euclidean distance are employed.

The advantage of using LBP is its ease of computation, low memory usage, and insensitivity to monotonic changes in grayscale. Therefore, it supports real-time processing without the need for high-performance hardware or heavy training processes, thereby making it especially ideal for light-weight face recognition systems for real-world applications such as security, automation, and embedded systems.

## Face Matching and Result Generation:

During the face matching stage of the system, the Local Binary Pattern (LBP) features of the detected input face are matched against stored feature vectors of the reference database. Every individual in the database is associated with an LBP histogram, comprising the local texture patterns of his/her face, which is a consistent and discriminative biometric signature.

In order to determine the degree of similarity between the input face and the reference face, the system employs the Euclidean distance measure. The method calculates the straight-line distance between two LBP feature vectors in n-dimensional space, and this results in a numerical value that indicates facial feature proximity. The reference face with the smallest Euclidean distance from the input face is selected as the best match. This approach achieves the best compromise between computational expense and overall performance, especially in real-time constraint situations.

After the optimal match is determined, the system proceeds to the result interpretation stage, where the recognition outcome is mapped into an identity and used to trigger pre-specified behavior in the target application domain. The recognized face will be capable of triggering a range of context-dependent responses, including but not limited to:

<u>Access Control:</u> Providing physical access by opening locked gates or smart doors to authorized personnel.

<u>Attendance Tracking:</u> Recording the presence of an individual with a timestamp in a school or organizational setting.

<u>Vehicle System Activation:</u> Providing secure, driver-specific access to vehicles or equipment by authenticating the driver's identity using facial recognition.

<u>Surveillance and Alerting:</u> The instant triggering of alerts or security notifications when an unauthorized, unknown, or blacklisted individual is detected.

This stage of the system shows the hidden incorporation of face recognition capabilities into practical security and automation devices. Employing modularity in design to enable it to scale and adapt leaves space for further development such as even more advanced classifiers (e.g., deep models), cloud-based service integration, and deployment to embedded or edge-computing platforms to enable wider practical use.

## Output Result from Matlab Simulation:


## Conclusion:

In conclusion, this project can successfully demonstrate the design and implementation of a simple face recognition system using MATLAB. The system uses standard computer vision techniques to deliver accurate and real-time face recognition, and it is both practical and cost-effective for numerous applications.

Going around the system core is the Haar Cascade classifier, a robust and reliable approach to object detection. The classifier can be employed to detect frontal human faces in static images and real-time streams with high accuracy. Its accuracy and speed make it extremely appropriate to utilize within real-time systems, especially within highly controlled environments with light and pose conditions being highly predictable.

Under recognition, the system applies Local Binary Pattern (LBP) features, which is a prevalent texture descriptor applied in the description of the local structure of a facial image. LBP conveys the correlation among pixels of a neighborhood so that the system can generalize good texture patterns using a unique individual. Pattern match-up enables the system to differentiate known correctly faces whose output can be safe face matching.

Ease of use and modularity were considered priorities during designing so that future customization and extension would be easy. Although the system would rely on traditional techniques, it is computationally efficient with satisfactory recognition accuracy. It would be permissible in terms of operation to employ it in the context of biometric attendance systems, controlled access systems, and video monitoring scenarios.