

Hand gesture

By team #13

Used algorithms

Hog

The Histogram of Oriented Gradients is a feature descriptor widely used in computer vision for object detection. It works by dividing an image into small, connected regions called cells and computes the gradient (magnitude and orientation) within each cell.

Support vector machine (classifier)

SVM is a supervised learning algorithm used for classification and regression tasks. In the project, SVM was employed as a classifier to distinguish between different hand shapes or gestures. After extracting features using HOG, SVM learns to create a decision boundary that separates the different classes of hand gestures. This involves training the classifier on a labelled dataset, where the features extracted by HOG act as input, and the corresponding hand gestures serve as the target labels.

Optical flow

Optical flow is a computer vision technique used to track the motion of objects within a sequence of images or video frames. It calculates the displacement of pixels between consecutive frames, providing information about the direction and speed of movement. In the project, optical flow played a role in segmenting the moving object, which, in this case, would be the hand.

Experiments

Experiment 1

This experiment involves a novel approach to enhance hand gesture detection through the combined use of the Canny edge detector and a colour mask. The Canny edge detector is applied to capture the prominent edges of the hand, providing a detailed representation of its contours. Simultaneously, a colour mask is employed to isolate pixels with colours surpassing a predefined threshold, effectively extracting regions with the predominant colour characteristics of the hand.

Following the application of these two methods, the project takes a unique step by merging the results in a manner that prioritizes the greater area identified in both images. This integration process ensures that the final output emphasizes the regions where both the Canny edge detector and the colour mask exhibit a significant presence. By giving precedence to the larger area, the project aims to enhance the robustness and reliability of hand gesture detection, effectively combining edge information and colour characteristics for a more comprehensive and accurate representation of the hand's features. This experiment showcases an innovative fusion of traditional edge-based techniques and colour-based segmentation, leveraging the strengths of both approaches to improve the overall performance of the hand gesture recognition system.



Experiment 2

This experiment introduces a unique dataset composition strategy, focusing on negative images containing only faces (133) and miscellaneous objects, contrasting with positive images specifically featuring hands (171,000). The project employs the optical flow technique in conjunction with Support Vector Machines (SVM), Histogram of Oriented Gradients (HOG), and a trained classifier to identify and classify hand gestures.



One notable challenge encountered during this experiment was incorrect results when the image background was black. To address this issue, the project utilized a classifier specifically designed to handle such scenarios. Despite initial attempts with histogram equalization, the experiment faced limitations in achieving the desired outcomes. Consequently, the project explored alternative techniques, employing contrast enhancement and a subtle Gaussian blur ($\sigma = 0.01$) to mitigate noise and generate smoother HOG features in the output.

This experiment underscores the importance of carefully curating datasets, especially in scenarios where negative images involve faces and diverse objects, posing challenges for accurate hand gesture recognition. The adaptation of the classifier to handle specific background conditions reflects the project's dedication to overcoming challenges and refining the system's performance.

Experiment 3

This experiment introduces an advanced methodology for hand gesture recognition, incorporating optical flow, object segmentation, and a hybrid classification system. The first step involves the application of optical flow to accurately track and segment moving objects within a sequence of images. This segmentation process effectively isolates dynamic elements, with a particular focus on the hand's movement.

Subsequently, a classification step is implemented to discern whether the moving objects are hands or other entities. This classification process involves two distinct algorithms: Local Binary Patterns (LBP) and k-Nearest Neighbours (kNN) with Histogram of Oriented Gradients (HOG). The LBP algorithm is initially employed to detect the texture of images, but its speed and accuracy are compromised due to poor orientation handling.

In contrast, the kNN algorithm, utilizing $k=3$ and HOG features, provides a more efficient and accurate classification of moving objects. Additionally, the project explores the Support Vector Machine (SVM) algorithm for classification, leveraging multiple feature descriptors, including Scale-Invariant Feature Transform (SIFT), LBP, and HOG. The trained model for these algorithms is created using a dataset comprising SIFT (1 GB, least accurate), LBP (517 MB, more accurate), and HOG (most accurate).

This comprehensive approach showcases the project's commitment to combining motion-based segmentation with a diverse set of texture and shape features for improved accuracy in hand gesture recognition. The exploration of multiple classification algorithms and feature descriptors demonstrates a thoughtful strategy to enhance the robustness and adaptability of the system, ultimately contributing to the project's overall success in accurately identifying and classifying hand gestures.

```
python3 -c "import cv2; import numpy as np; from src import handgesture_movement_detector; detector = handgesture_movement_detector.HandGestureMovementDetector(); detector.load_model('models/knn_model.pkl'); detector.load_features('features/knn_features.pkl'); detector.test('test_images/test_image.jpg'); print('Test Accuracy: 99.47%')"
```

kNN accuracy

```
small numerical differences between adjacent pixels are present. It is recommended to use this function warnings.warn(  
Test Accuracy: 100.00%
```

LBP accuracy

```
python3 -c "import cv2; import numpy as np; from src import handgesture_movement_detector; detector = handgesture_movement_detector.HandGestureMovementDetector(); detector.load_model('models/lbp_model.pkl'); detector.load_features('features/lbp_features.pkl'); detector.test('test_images/test_image.jpg'); print('Test Accuracy: 97.20%')"
```

Sift accuracy

```
Test Accuracy: 99.76%
```

SVM accuracy

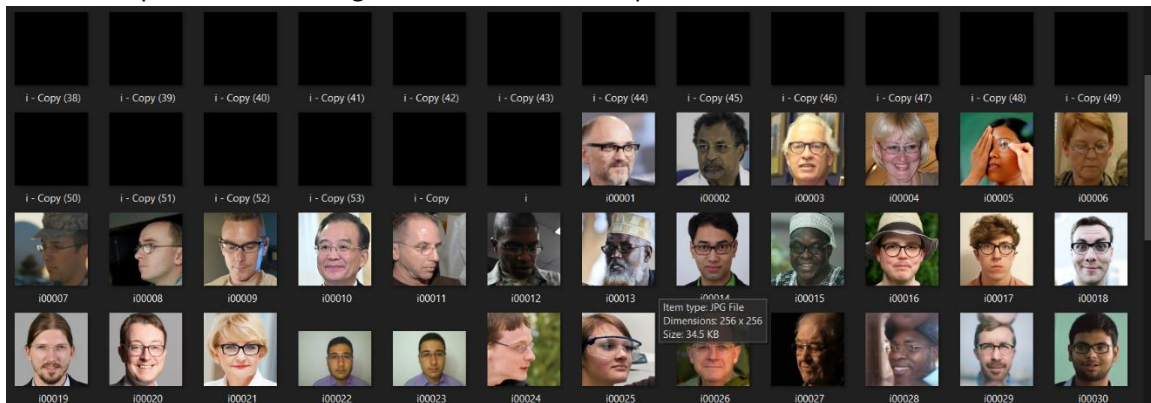
Classifier

The classifier described is trained for hand gesture recognition and is designed to distinguish positive instances, representing various hand gestures, from a diverse set of negative instances that include faces, black images, elevators and walls, halls, and people in different scenarios. The training dataset is meticulously curated to ensure the classifier's ability to generalize and accurately classify hand gestures in challenging conditions.

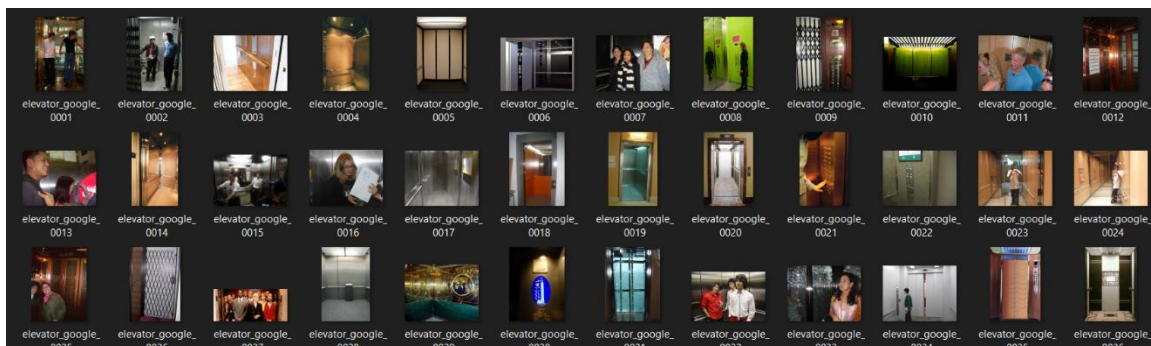
Negative Instances: (865 images)

Faces (133): Negative instances containing only faces are included to prevent the classifier from associating face features with positive hand gestures.

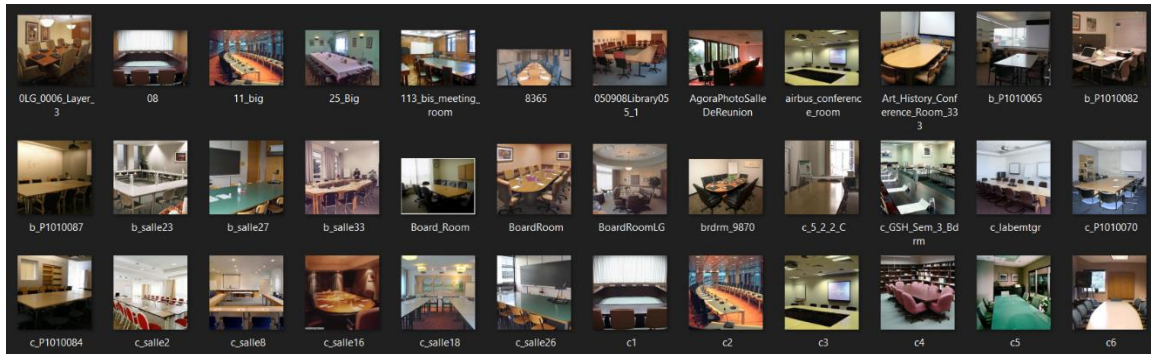
Black Images (50): Instances with black backgrounds are introduced as negative examples to avoid false positives if the hog doesn't extract the important features.



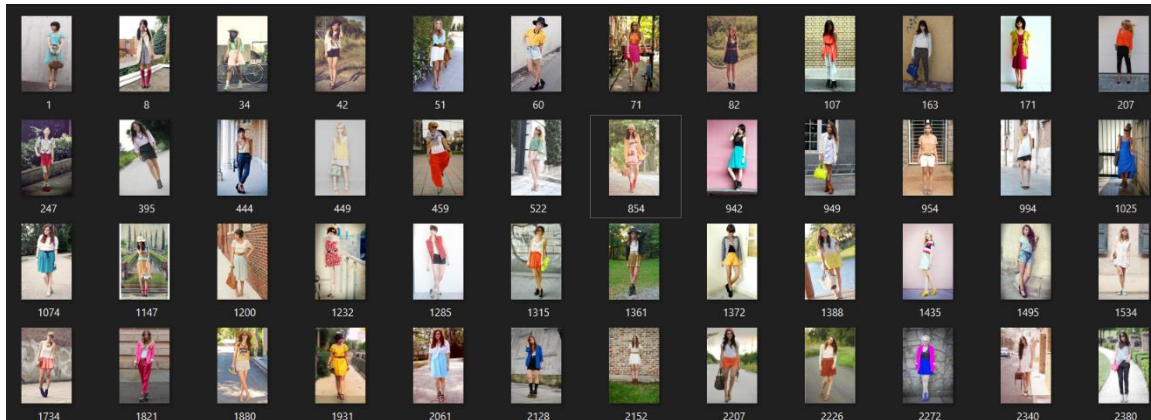
Elevators and Walls (102): Images featuring elevators and walls serve as negative examples, ensuring that the classifier doesn't misclassify architectural elements as hands.



Halls (233): Negative instances of halls are included to prevent the classifier from identifying walls as positive hand gestures.

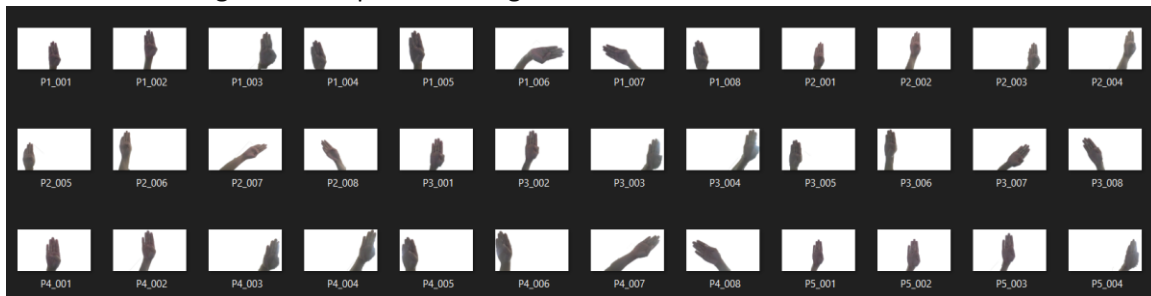


People (168): Images with people in the background are introduced as negative examples, preventing the classifier from associating people with positive hand gestures.



Positive Instances: (2828 images)

Palms (400): Instances featuring isolated palms are included as positive examples to ensure that the classifier recognizes this specific hand gesture.



Hand with Fingers (900): Positive instances with hands and distinct fingers are included to train the classifier to recognize the detailed shape of a hand with articulated fingers.

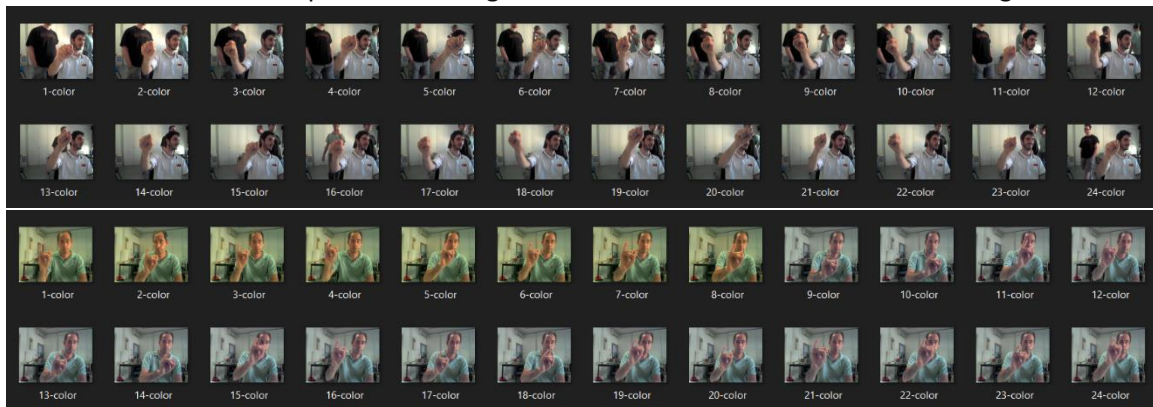


Low View of Fingers (200): Instances featuring hands captured from a different camera view are included, ensuring that the classifier can handle variations in perspective.



Bad Quality Arm Images (8): A small set of images with poor camera quality is included as positive examples, teaching the classifier to tolerate lower image quality.

Various People with Faces and Hands (1320): Diverse images of people with their faces and hands are included to help the classifier generalize to different individuals and backgrounds.



Conclusion

The hand gesture recognition project employs a versatile approach, combining edge detection, optical flow, and various classifiers with distinct feature descriptors. SVM, particularly effective with HOG due to its strength in high-dimensional spaces, emerges as the optimal choice. The project addresses challenges like black backgrounds through specialized classifiers and pre-processing techniques, showcasing adaptability. In summary, the project demonstrates a robust and effective methodology, highlighting the powerful combination of SVM and HOG for accurate hand gesture recognition in diverse environmental conditions.

Work division

Name	Roles
Ibrahim Tarek	<ul style="list-style-type: none">• Optical flow to segment hand• Experiment 1• Experiment 3
Mahmoud Ossama	<ul style="list-style-type: none">• Experiment 2• Train SVM with hog (used in the project)
Ahmed Omar	<ul style="list-style-type: none">• Parallelism of the code• Keyboard
Malek Hossam	<ul style="list-style-type: none">• Implementation of optical flow• Implementation of hog