IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

OBJECT DETECTION USING HAAR CASCADE MACHINE LEARNING ALGORITHM

Gowsikraja P [1], Thevakumaresh T [2], Raveena M [3], Santhiya.J [4], Vaishali.A.R.R[5]
Assistant Professor, Department of C.S.E, Jansons Institute of Technology, Coimbatore, India[1]
UG Students, Department of C.S.E, Jansons Institute of Technology, Coimbatore, India [2 - 5]

Abstract:
Computer vision library (OpenCV)object classifier. This is a problem that can be overcome with Haar cascade .Object recognition is an important feature of computer science. Object recognition penetrates deeper and deeper into the common territory of the information society, and is useful where it is needed. This paper describes one such possibility using the Haar cascade classifier. Images are usually processed at a lower level first to improve image quality, such as noise reduction. The image is then processed at a higher level, for example to recognize the pattern. The system detects the object in question by moving window over the image. Each stage of the classifier marks a particular area as either positive or negative, as defined by the current position of the window. Positive means that the object was found, negative means that the specified object was not found in the image. The focus is on case studies of vehicle detection and counting systems and the potential in semi-closed areas as a statistical feature. The purpose of the system to be developed is to make daily life easier and richer.

I. Introduction

Haar cascade is a machine learning –based approach where a lot of positive and negative image are used train the classifier. Haar cascade classifiers are an effective way for object detection.
Defining a custom object for an image is called object detection. This task can be performed using several techniques, but with the hair cascade, which is the easiest way to discover objects.
Object Detection is a computing technology related to computer vision, image processing, and deep learning that handles the detection of object instances in images and videos. In this article, we will use the so-called Haar Cascade to Perform object discovery. Haar Cascade is an algorithm that can detect objects in an image regardless of the size or position of the objects in the image. .
This algorithm is not very complicated and can be executed in real time. You can train the Haar Cascade Detector to detect various objects such as cars bicycles, buildings and fruits.
Haar Cascade uses Cascade windows to Calculate the characteristics of each window and try to classify them as object.

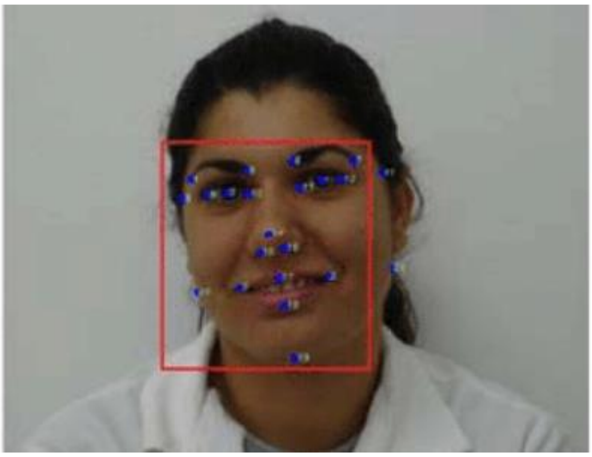
Keywords
Cascades,Yolo,CNN,Haar features.

Related Work

Cascade object detector system object detects objects in images by sliding a window over the image. The detector then uses a cascade classifier to decide whether the window contains the object of interest. The size of the window varies to detect objects at different scales, but its aspects ratio remains fixed. Unlike other biometrics, facial recognition is non-invasive and does not require a person to have physical contact with the system, making it a highly acceptable biometric.The automatic visual system applied to face recognition can be divided into four steps: face recognition, image preprocessing, feature extraction, and matching. Face recognition is a difficult task when faces form objects of a similar class and features such as eyes, mouth, nose, and chin generally have the same geometry. The captured facial image can be preprocessed to compensate for changes in lighting Object mining is the process of obtaining a geometric or vector model of a set of important functions displayed on a surface Functional mining can be divided into three approaches: holistic, functional based, hybrid. With the contribution of Viola Jones' object detection framework, the introduction of image capture has improved face detection speed. Implementation of this framework (such as) B. Open CV provides different face classifiers created by authors using different datasets during training. The performance and reliability of these classifiers varies greatly. The performance of the classifier has been exclusively evaluated and their accuracy has been tested. The goal here is to find the sum of all the image pixels in the darkest area of the hair feature and the sum of all the image pixels in the lightest area of the hair feature. And discover the difference between them. Here, if there is an edge that separates the dark pixels on the right side and the bright pixels on the left side of the image, the hair value will be close to 1. That is, when the price approaches the hair value of 1, edges are detected. .. In the above case, for example, the hair value is far from 1, so there is no border.

Existing work

Compared to previous YOLO object detection algorithm approaches that reuse classifiers to perform detection, YOLO proposes the use of an end-to-end neural network that simultaneously generates bounding box predictions and class probabilities by taking a radically by taking a radically different approach to object detection, YOLO achieves best results with performance far superior to other real-time object detection algorithm.



In addition to improving the accuracy of predictions (compared to real-time object dectors) and the intersection of joins in the bounding box, YOLO has its own speed advantage. YOLO is a much faster algorithm than other algorithms and runs at up to 45 FPS. YOLO seems to be the best algorithm you can use if you need to solve an object detection problem, but with some limitations YOLO is restricted to each mesh detecting only one object, which makes it difficult to detect and separate small objects in images displayed in groups. As a result, YOLO finds it difficult to detect and find small object that that often appear in groups such as: B Ali. The YOLO algorithm works by dividing the image into N grids. The area of each grid is SxS. Each of these N grid is responsible for recognizing and identifying the contained object. . Therefore, these grids predict the coordinates of the bounding cell B relative to the cell coordinates, as well as the name of the feature and the probability that the feature will be present in the cell. This process significantly reduces the calculation because the detections and detections are handled by the cells in the image, but because many cells predict the same object with the same prediction, many duplicate predictions are generated. increase.

Drawbacks

- ✓ It has a relatively low recall rate compared to high-speed R_CNN and has many localization errors.
- ✓ Neighbors are difficult to detect because each grid can only provide two limited cells.
- ✓ Each mesh can only detect one object, which makes it difficult to detect small objects and slow performance in small group of objects.
- ✓ The main error in YOLO is due to localization, as the scale of the bounding

box is completely learned from the data and YOLO raises errors in the bounding box of anomalous scale.

- ✓ The frame rate is lower than the hair cascade.
- ✓ The level of accuracy is still lacking.
- ✓ The detection level is low.

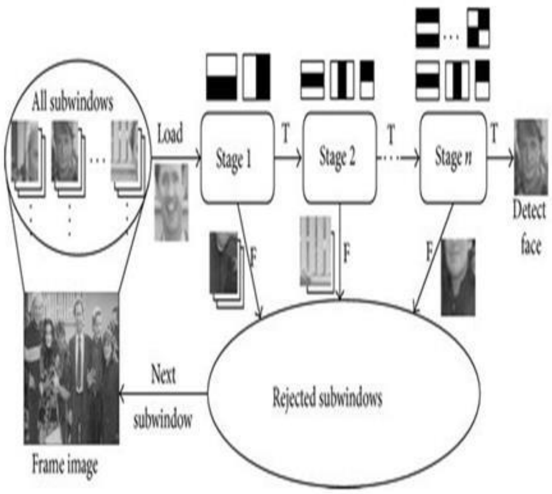
Proposed System

- ✓ Build machine learning applications for object discovery using Python, Open CV, Flask, and Haar cascade functions.
- ✓ By using the Hair Cascade algorithm, you can use the edge or line detection feature to detect blurry or dark discussion
- ✓ The algorithm is given many positive images consisting of faces and many negative images that do not include the face to be trained.

Result and Discussions

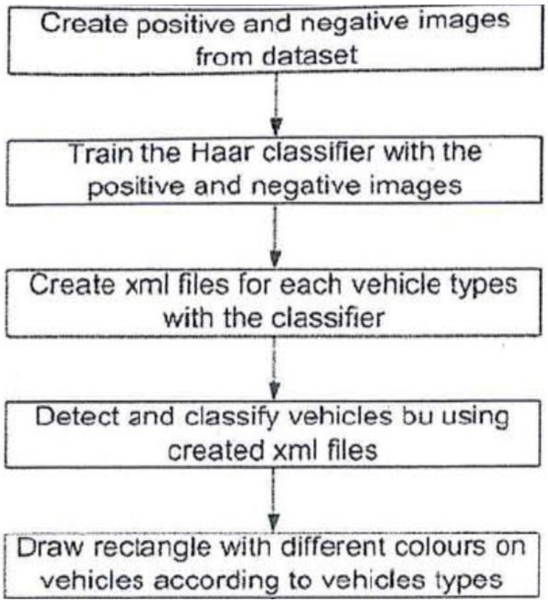
The training set was captured from the top and front of the vehicle. You can see the vehicle media type in the xml file used. The XML file is generated after the classifier has been trained. Vehicles leave the lane depending on the vehicle type detected by horizontal and vertical coordinates. For example, a truck that is in the left lane instead of the right lane is a vehicle with a disability in the system. Similarly, a vehicle driving at the median is the fault of the driver of the system. The system draws a rectangle of the vehicle based on the vehicle type. Haar Cascade is a classifier developed by the author to detect and track objects in images. To train a classifier, you need a positive image that contains the objects found in the image and a negative image that does not contain the searched objects. The classifier analyzes the features of a positive image and uses the sum of the values in the black and white areas of the geographic feature to generate a specific target value. Physically. The classifier attempts togenerate the best possible target value for object detection and tracking by resizing the object. Function is a weak classifier. Just for them, they cannot be exact classifiers.

Positive and negative images are used to train the classifier. Train the classifier by presenting a unique positive image based on the vehicle type.



Hair features continuously traverse the image from top left to bottom right looking for specific features. This is just a representation of the entire concept of hair transfer function.

In real life, the hair feature iterates over each pixel of the image. In addition, all possible dimensions of hair features apply. Hair objects move continuously from top left to bottom right in the image to search for a particular object. This is just a representation of the entire concept of hairtransfer function. In real work, the hair feature iterates over every pixel in the image. In addition, all possible dimensions of hair features apply. They usually fall into three categories, depending on the feature you are looking for. The first set consists of two rectangular objects for finding horizontal or vertical edges. The second set of three rectangular features serves to determine if there is a bright area surrounded by dark areas on either side, or vice versa. The third set of four rectangular features serves to find changes in pixel intensity across the diagonal.



Conclusion

This study uses image processing methods to detect and track false drivers in road traffic. The Haar Cascade Classifier is used to detect vehicles. The axis coordinates of the vehicle recognized in the image are evaluated and an attempt is made to identify the failed vehicle based on these axis coordinates. The accuracy rate of the system achieves a very good value. This study shows that the Haar cascade classifier is a good candidate for object detection.

References

[1] Y. Amit, D. Geman, and K. Wilder.Joint induction of shape features and tree classifiers, 1997.

[2] Anonymous. Anonymous.In Anonymous, 2000.

[3]F. Crow. Summed-area tables for texture mapping. In Proceedings of SIGGRAPH, volume 18(3), pages 207–212, 1984.

[4] F. Fleuret and D. Geman.Coarse-to-fine face detection.Int. J. Computer Vision, 2001.

[5] William T. Freeman and Edward H. Adelson. The design and use of steerable filters. IEEE Transactions on Pattern Analysis and Machine Intelligence, 13(9):891– 906, 1991.

[6] Yoav Freund and Robert E. Schapire.A decision-theoretic generalization of on-line learning and an application to boosting. In Computational Learning Theory: Eurocolt '95, pages 23–37. Springer-Verlag, 1995.[7] H. Greenspan, S. Belongie, R. Gooodman, P. Perona, S. Rakshit, and C. Anderson.Overcomplete steerable pyramid filters and rotation invariance. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 1994.

[8] L. Itti, C. Koch, and E. Niebur.A model of saliency-based visual attention for rapid scene analysis. IEEE Patt. Anal.Mach. Intell., 20(11):1254–1259, November 1998.

[9] Edgar Osuna, Robert Freund, and Federico Girosi. Training support vector machines: an application to face detection. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 1997.

[10] C. Papageorgiou, M. Oren, and T. Poggio.A general framework for object detection.In International Conference on Computer Vision, 1998.

[11] D. Roth, M. Yang, and N. Ahuja. A snowbased face detector.In Neural Information Processing 12, 2000.

[12] H. Rowley, S. Baluja, and T. Kanade.Neural network-based face detection.In IEEE Patt.Anal. Mach. Intell., volume 20, pages 22–38, 1998.

[13] R. E. Schapire, Y. Freund, P. Bartlett, and W. S. Lee.Boosting the margin: a new explanation for the effectiveness of voting methods. Ann. Stat., 26(5):1651–1686, 1998.

[14] Robert E. Schapire, Yoav Freund, Peter Bartlett, and Wee Sun Lee.Boosting the margin: A new explanation for the effectiveness of voting methods.In Proceedings of the Fourteenth International Conference on Machine Learning, 1997.[15] H. Schneiderman and T. Kanade. A statistical method for 3D object detection applied to faces and cars. In International Conference on Computer Vision, 2000.