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Review on Cars and Pedestrian Detection

Akshay D. Deshmukh[1*], Sanchit Gupta[2], Ambalika Donge[3], Piyush Katolkar[4], Abhishek Tipre[5], Rakesh A. Bairagi[6]

[1,2,3,4,5]*Student, Department of Computer Science and Engineering, Govindrao Wanjari College of Engineering and Technology, Nagpur, India*

[6]*Assistant Professor, Department of Computer Science and Engineering, Govindrao Wanjari College of Engineering and Technology, Nagpur, India*

***Abstract*: Electronic systems that can identify pedestrians in front of a vehicle and forecast vehicle-to-pedestrian collisions must be specified, implemented, and evaluated. Vehicle-to-pedestrian collisions were categorised into eleven different scenarios in this study. The key features of vehicle-to-pedestrian collisions have been established. The statistical behaviours of the various systems involved were modelled (vehicle, pedestrian, environment, and advanced driver assistance gadgets). Then, for crucial automobile and pedestrian road conditions, Monte-Carlo simulations were run. The created simulation tool enables the evaluation and validation of possible innovative systems' performance. Intelligent video surveillance, intelligent transportation, automotive autonomous driving, and driver-assistance systems all use cars and pedestrian detection. For the implementation of automobiles and pedestrian detection in a video segment, we chose OpenCV as the programming tool. This programme will be written in Python and will make use of OpenCV.**

***Keywords*: OpenCV, machine learning, python, pedestrian detection, vehicle detection, computer vision.**

1. Introduction

In the subject of computer vision, there has been a lot of progress recently. Using the camera in video sequences, object tracking is the most frequent method for recognising moving things beyond time. Object tracking's major goal is to link the target objects' shape or features, as well as their location, in successive video sequences. As a result, object classification and detection are critical for object tracking in computer vision applications. Furthermore, tracking is the first stage in recognising any moving objects in the frame. Furthermore, the observed objects can be classified as swaying trees, birds, humans, automobiles, and so on. Although object tracking using video sequences is a difficult task in image processing, it is possible. Occlusion of the object to scene, object to object, complex object motion, real-time processing needs, and the inappropriate or distorted shape of the item appear to be responsible for a number of other difficulties. However, this form of tracking is currently employed in a variety of settings, including traffic monitoring, robot vision, surveillance and security, video communication, and public venues such as subway stations, airports, mass gatherings, and animation, to name a few. As a result, the application requires an ideal trade-off between processing, communication, and network accuracy. The number and type of cooperation performed among cameras for data gathering, dispensing, and processing to validate decisions and eliminate estimation mistakes and ambiguity is what drives computing and communication income. As a result, tracking can be defined as the process of identifying an object's orientation over time as the object moves across a scene. Because of the proliferation of high-powered computers and the growing demand for automated surveillance systems and other applications, object tracking is becoming increasingly important in the field of computer vision. It is mostly employed in the areas of automated surveillance, robotics monitoring, human-machine interface, motion-based recognition, vehicle navigation, traffic monitoring, and video indexing these days. A large number of these applications necessitate highly reliable and efficient tracking algorithms that adhere to real-time constraints and are challenging and sophisticated in terms of object movement, scale and appearance, scene illumination, and occlusion. The outcome of object tracking could be influenced by a discrepancy in one of the parameters. A vast variety of ways have been offered to address the above-mentioned challenges and others in object tracking. Cars and pedestrians will be the targets of this object tracking programme. The ability of machines to recognise suspicious objects and further identify their actions in a given context is a critical component of allowing machines to communicate with people in an effective and simple manner. The existing method for analysing and detecting suspicious objects usually necessitates the use of an exceptional marker attached to the suspicious object, which precludes the use of extensive technology. We strive to incorporate automobiles and pedestrian detection in this paper, as well as provide efficiency by including a time library.

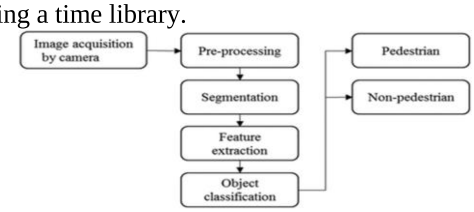


Fig. 1. Flowchart of system

*Corresponding author: akshaydesh750@gmail.com

2. Literature Survey and Review

In the previous study the papers were only focusing on object detection or object tracking. (Ben Ayed et al., 2015; Najva and Bijoy, 2016; Ramya and Rajeswari, 2016; Risha and Kumar, 2016; Shen et al., 2013; Soundrapandiyan and Mouli, 2015; Viswanath et al., 2015) ,Object tracking (Bagherpour et al., 2012; Foytik et al., 2011; Lee et al., 2012; Poschmann et al., 2014; Yilmaz et al., 2006; Zhang et al., 2016) and Object recognition (Chakravarthy et al., 2015; Gang et al., 2010; Ha and Ko, 2015; Nair et al., 2011) for tracking the object using video sequences with the help of camera. These are discussed as follows. The basic flow diagram of an object tracking shown in shown in figure 2.

Table 1
Comparative study of object detection techniques

Object DMethod		Basic Principle	ComputationalTime	Accuracy	Comments
Temporal Differencing		Pixel-wise Subtraction of Current & Background frame	Low	High	Easy to implement (Chate et al.,2012; Mohan and Resmi, 2014)
					Sensitive to dynamic changes(Haritaoglu et al., 2000)
					Needs background frame with still objects (Mohan and Resmi,2014)
Background Subtraction	Frame Differencing	Current frame is subtracted from background frame	Low to Moderate	Moder ate to High	Simplest background Subtraction(Aldhaheri and Edirisinghe, 2014; Haritaoglu et al., 2000)
					Cannot be used forreal-timeapplications (Mohan and Resmi, 2014)
	Approximate Median	Simple subtraction between median frame & test frame	Low to moderate	Moderate	Noneed foradequatebackground modeling (Aldhaheri and Edirisinghe, 2014)
					Requires a buffer with recent pixel values (Aldhaheri andEdirisinghe, 2014)
	RunningGaussian Average	Based on Gaussianprobability densityfunction of pixels	Moderateto high	Moderate	Much suitable forreal-time applications (Aldhaheri andEdirisinghe, 2014)
					Statistical calculations consumesmore time
	Mixture of Gaussian	Basedon multimodal distribution	Moderate to high	Moder ate to high	Low memory requirement(Zhiqiang et al., 2006)
					Cannot cope up with objects aswell as noise(Tao Zhang et al., 2010)
Optical Flow		Uses optical flow distribution characteristics of pixels of object	Moderate to high	High	This approach offers entire moving data(Krishna et al., 2011) however require more calculations

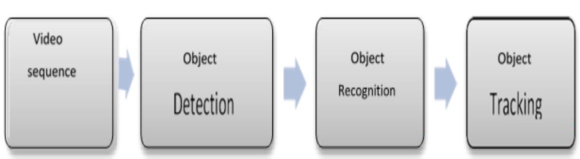
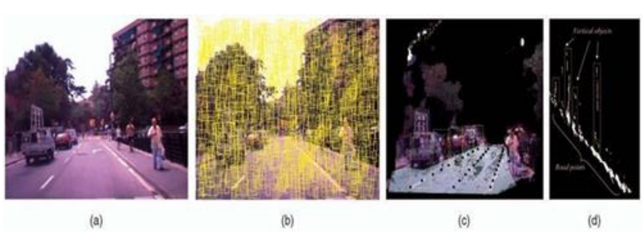


Fig. 2. The basic flow diagram of object tracking



The above diagram or figures represent foreground segmentation schemes. Here, (a) Original image. (b) Exhaustive scan (just showing 10 percent of the ROIs). (c) Sketch of road scanning after road fitting in Euclidean space. (d) Results of v- disparity applied to the same frame.

3. Object Detection Studies

Object detection approaches such as template matching and simple part-based models were used in the early days [e.g., Fischler and Elschlager (1973)]. Later, statistical classifier-based approaches (e.g., Neural Networks, SVM, Adaboost, Bayes, etc.) were introduced [e.g., Osuna et al. (1997), Rowley et al. (1998), Sung and Poggio (1998), Schneiderman and Kanade (2000), Yang et al. (2000a,b), Fleuret and Geman (2001), Romdhani et al. (This first successful family of object detectors, all based on statistical classifiers, laid the groundwork for the majority of subsequent research in terms of training and evaluation procedures, as well as classification methodologies. In order to detect the things showing in the image at multiple scales and positions, most object detection systems use the same basic strategy, known as sliding window: an exhaustive search is used to detect the objects appearing in the image at different scales and places. This search employs a classifier, which is the detector's fundamental component and determines whether a particular image patch relates to the item or not. Given that the classifier only works at a certain scale and patch size, many downscaled versions of the input image are created, and the classifier is used to classify all possible patches of the given size for each of the downscaled versions.

1) Object Detection Approaches and their comparison

Object detection methods can be grouped in five categories, each with merits and demerits: while some are more robust, others can be used in real-time systems, and others can be handle more classes, etc.

Object detection is important in various applications, but especially in video surveillance applications where things are discovered using video footage (Amandeep and Goyal, 2015). In Figure 3, various forms of object detection are depicted.

Method	Coarse-to-fine and boosted classifiers	Dictionary based	Deformable part-based models	Deep learning	Trainable image processing architectur
Accuracy	++	+=	++	++	+=
Generality	==	++	+=	++	+=
Speed	++	+=	==	+=	+=
Advantages	Real-time, it can work at small resolutions	Representation can be shared across classes	It can handle deformations and occlusions	Representation can be transfered to other classes	General-purpose architec that can be used is sever modules of a system
Drawbacks/ requirements	Features are predefined	It may not detect all object instances	It can not detect small objects	Large training sets specialized hardware (GPU) for efficiency	The obtained system may Too specialized for a particular setting
Typical applications	Robotics, security	Retrieval, search	Transportation pedestrian detection	Retrieval, search	HCI, health, robotics

Accuracy: ++, High; +=, Good; ==, Low.
Speed: ++, real-time (15 fps or more); +=, online (10–5 fps); ==, offline (5 fps or more).
Generality: ++ (+=), applicable to many (some) object classes; ==, depend on features designed for specific classes.

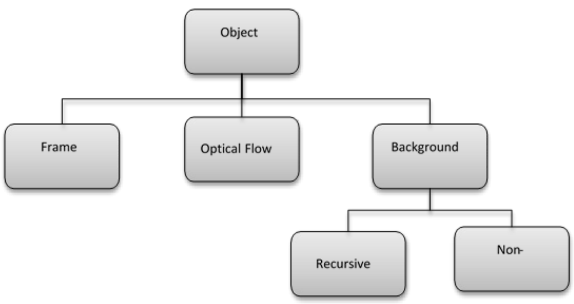
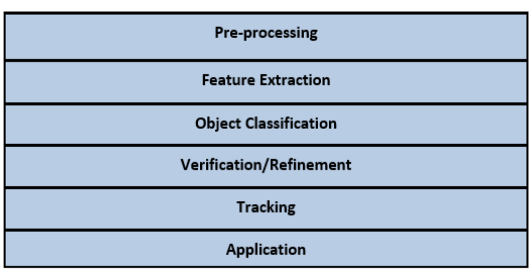


Fig. 3. Types of object detection method

4. Workflow of Cars and Pedestrian Detection



1) Pre-processing

Pre-processing includes a variety of duties that are required at the start of the process, such as exposure time, gain changes, and camera calibration, to name a few. Some low-level modifications are made that aren't generally documented in ADAS literature, and some researchers have used these systems to target visual improvement. There are two methods for doing so: monocular and stereo vision.

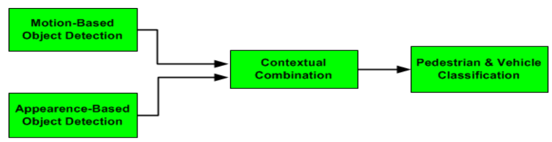
2) Feature Extraction

We can classify the different features as:

- General features: Color, texture, and shape are examples of general qualities that are not application specific. They can be further classified into the following categories based on the level of abstraction: Features at the pixel level: Color and position are examples of features that are determined at each pixel.
- Local features: Local features are those features that are calculated over the results of subdivision of the image band on image segmentation or edge detection.
- Global features: These are the features that are calculated over an entire image or just regular sub-area of an image.
- Domain-specific features: Domain-specific features are nothing but application dependent features such as fingerprints, human faces and also conceptual features. These features are nothing but a synthesis of low-level features for a specific domain.

All available features are divided into two categories: low-level features and high-level features. Low-level features are retrieved from the source images, whereas high-level features are extracted from low-level features.

- Object Classification



- Verification/Refinement

A tracking module is used by the majority of advanced systems to track recognized autos and people over time. This step is important for several reasons, including avoiding false detections over time, predicting future positions of cars and pedestrians and thus providing pre-candidates to the foreground segmentation algorithm, and, at a higher level, inferring useful information about pedestrian and car behavior (e.g., walking/driving direction).

3) Tracking

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4) Application

Pedestrian detection is an essential and significant task in any intelligent video surveillance system, as it provides the fundamental information for semantic understanding of the video footages. It has an obvious extension to automotive applications due to the potential for improving safety systems. For avoiding accidents and also avoiding traffic problems using smart techniques this system is useful.

5. Conclusion

Review of numerous object detection, tracking, recognition algorithms, feature descriptors, and segmentation methods based on video frames and various tracking technologies, as well as our suggested automobiles and pedestrian detection system are presented in this work. This application outperforms similar apps in terms of accuracy and efficiency. We have also explored numerous restrictions and advancements in relation to this proposed use, but it is now far too complex.

6. Future Scope

We could create complicated video sequence simulations and test them using the same tracking algorithm. In the expected case, moving objects are occluded by an item of the same colour or by a larger occlusion with a longer occlusion time. The tracking algorithm will be more efficient and functional if the number of objects is increased. For each individual pixel's intensity, weight parameters could be applied. In any image, if the intensity value is allocated as foreground based on the current frame, the likelihood that the foreground also has similar pixel coordinates is reduced, allowing the BG weightage for the pixel to be set to the lowest value possible. By adding a weightage that is lower than the beginning value, the previous pixel value can be removed with the least likelihood rather than the evolved scene.

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