ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 6, June 2017

Multiple Sensor Fusion and Classification for Moving Object Detection and Tracking

Shubham V. Avachar, Dr. S. D. Lokhande

M. E Student, Dept. of Electronics & Telecommunication, Sinhgad College of Engineering, Pune, India

Dept. of Electronics & Telecommunication, Sinhgad College of Engineering, Pune, India

ABSTRACT: The précised detection and classification of moving objects is a important aspect of advanced driver assistance systems. By including the object classification from multiple sensor detections as a major component of the object's representation and the perception process, we can improve the perceived model of the environment. At first, we define a composite object representation to include information in the main object's description. At Second, we propose a complete perception fusion architecture based on the framework to solve the detection and tracking of moving objects problem by adding the composite representation and uncertainty events management. At last, we integrate our fusion approach in a real-time application inside a vehicle demonstrator which includes main sensors: radar and camera. We test our fusion system using real data from different driving scenarios and more focusing on four objects of interest: like pedestrian, truck and other vehicles.

KEYWORDS: Intelligent vehicles, sensor fusion, classification algorithms, vehicle detection, vehicle safety.

I. INTRODUCTION

Intelligent vehicles have moved from being a robotic application of tomorrow to a current area of extensive research and development. The most striking characteristic of an intelligent vehicle system is that it has to operate in increasingly unstructured environments, which are inherently uncertain and dynamic. ADAS help drivers to perform complex driving tasks to avoid dangerous situations. Assistance tasks include: warning messages in dangerous driving situations, activation of safety devices to mitigate imminent collisions, autonomous maneuvers to avoid obstacles, and attention-less driver warnings. Perceiving the environment involves the selection of different sensors to obtain a detailed description of the environment and an accurate identification of the objects of interest. Vehicle perception is composed of two main tasks: simultaneous localization and mapping (SLAM) which generates a map of the environment while simultaneously localizing the vehicle within the map given all the measurements from sensors; and DATMO which detects and tracks the moving objects surrounding the vehicle and estimates their future behaviour. Fig. 1 shows the main components of the perception task.

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 6, June 2017

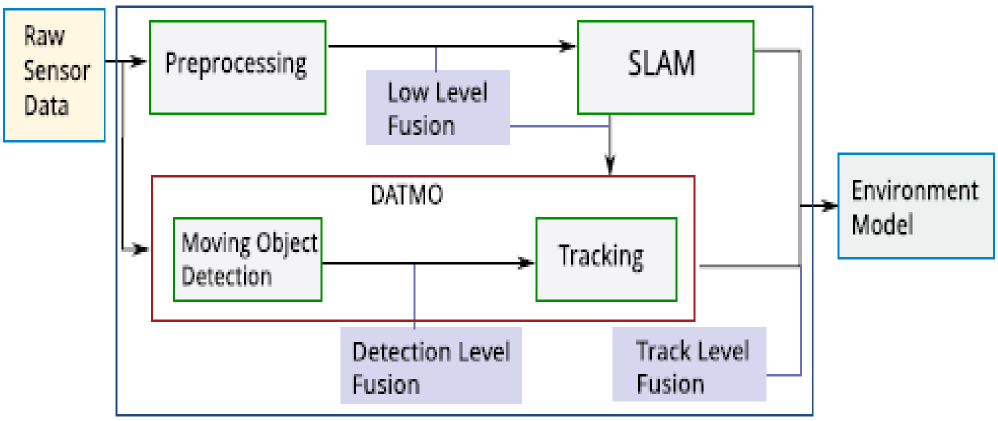

Fig.1. Fusion levels within the SLAM and DATMO components interaction.

II. LITERATURE REVIEW

C. Mertz et al., “Moving object detection with laser scanners,” J. Field Robot., vol. 30, no. 1, pp. 17–43, Jan. 2013. DATMO can be employed on avariety of platforms with different kinds of 2D and 3D laserscanners. The data from multiple scanners can be combinedon the raw data level, on the segment to object level, or onthe object level. The system is able to track on the orderof 100 objects simultaneously. The applications that usedour DATMO included a collision warning system, pedestriandetection and classification, autonomous driving, humantrack learning and prediction, and input to a dynamicplanner. We have also characterized the accuracy and thelimitations of the system. Our DATMO is now a tool with which we can buildmany more future applications. Nevertheless, there are areaswhere our DATMO can be improved. It would be desirableto have a more systematic way of optimizing the configurationparameters of DATMO for particular purposes.There could also be a use for a greater variety of each of thesub algorithms: ground estimation, segmentation, featureextraction, association, motion prediction, stochastic filters,and classification. A particularly interesting and challenging topic is dynamicplanning, i.e., planning in environments with movingobjects. Such planning would already be difficult ifthe sensors gave a perfect representation of the environment.But the additional challenge for the planner is todeal with the uncertainties that will come from DATMO.For DATMO, on the other hand, the challenge is to makethe right tradeoffs between different errors [4].

M. Perrollaz, C. Roy, N. Hauti, and D. Aubert, “Long range obstacle detection using laser scanner and stereovision,” in Proc. IEEE Intell. Veh.Symp., 2006, pp. 182–187. in this paper an innovative method for long range road obstacles detection. In particular, we presented and compared three obstacle confirmation criteria which have distinct advantages and drawbacks. In parallel, a range enhancement technique using numerical zoom has been presented. It is efficient and allow to take advantage of higher resolution images without increasing the computation time. The whole system is successfully used in the LIVIC experimental vehicles for collision-mitigation purpose. This system has very good performances and the remaining false alarms (two for 500 km driving) are due to very complex urban situations. Thanks to the range enhancement, it is also possible to develop stop & go and interdistances management applications for urban highway. The performances of these last systems are currently assessed [7].

M. Skutek, D. Linzmeier, N. Appenrodt, and G. Wanielik, “A precrash system based on sensor data fusion of laser scanner and short range radars,” in Proc. IEEE 8th Int. Conf. Inf. Fusion, 2005, pp. 1287–1294. In this paper a PreCrash application based on sensor data fusion was presented. As sensors a laser scanner and two short range radars, mounted in the front of a test car, are used. The focus of this paper was to give an overview about the whole system structure and the requirements of a PreCrash application. The requirements of the application and also the car environment influence directly the choice, which sensors will be used. The sensor data fusion in a competitive way uses

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 6, June 2017

the redundancy given by similar data of several sensors based on different physical basics to increase the certainty of object identity and crash-relevant object information. The described data synchronization problem makes the fusion step more difficult and represents an additional source of error. A second source of error - possible sensor failures, for example coming from dust, must be considered. Since the complexity of the environment is very big and models for misbehavior are hard to find, an approach, based on simple statistical functions was developed [8].
P. Smets, “Data fusion in the transferable belief model,” in Proc. IEEE 3rd Int. Conf. FUSION, 2000, vol. 1, pp. 21–33. In many applications, the information needed to applythe probability approach is unfortunately not available.One could of course try to fit the missing informationby some ‘educated guesses’. Quality of the results is ofcourse directly related to the quality of the ‘fixing’.On the contrary, the belief function model is welladapted to work with the information as really available.This power comes from the ability of belief functionsto represent any form of uncertainty: full knowledge,partial ignorance, total ignorance (and evenprobability knowledge). Probability functions do nothave such expressiveness power. Equi-probability isnot full ignorance; it is already a quite precise form ofknowledge [5].
R. Chavez-Garcia, T. D. Vu, and O. Aycard, “Fusion at detection level for frontal object perception,” in Proc. IEEE IV, Jun. 2014, pp. 1225–1230. In this paper, presented a multiple sensor fusion framework at detection level based on DS theory to represent class hypotheses, associate object detections and combine evidence from their position and appearance. Even if we use a specific set of sensors to feed our proposed fusion approach, it can be extended to include several sources of evidence. The proposed method includes uncertainty from the evidence sources and from the object classification. Several experiments were conducted using datasets from real driving scenarios. We showed a quantitative comparison between the presented fusion approach at detection level and a fusion approach at tracking level. These experiments showed improvements in the reduction of mis-classifications and false detections of moving objects [2].
P. Dollár, C. Wojek, B. Schiele, and P. Perona, “Pedestrian detection: An evaluation of the state of the art,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 34, no. 4, pp. 743–61, Apr. 2012. Pedestrian detection is a key problem in computer vision, with several applications that have the potential to positively impact quality of life. In recent years, the number of approaches to detecting pedestrians in monocular images has grown steadily. However, multiple data sets and widely varying evaluation protocols are used, making direct comparisons difficult. This paper shows experiments that despite significant progress, performance still has much room for improvement. In particular, detection is disappointing at low resolutions and for partially occluded pedestrians [3].

III. PROPOSED METHODOLOGY

The below figure is the block diagram of the proposed system which is further divided into various parts. The block diagram shows the and classification of the moving object.

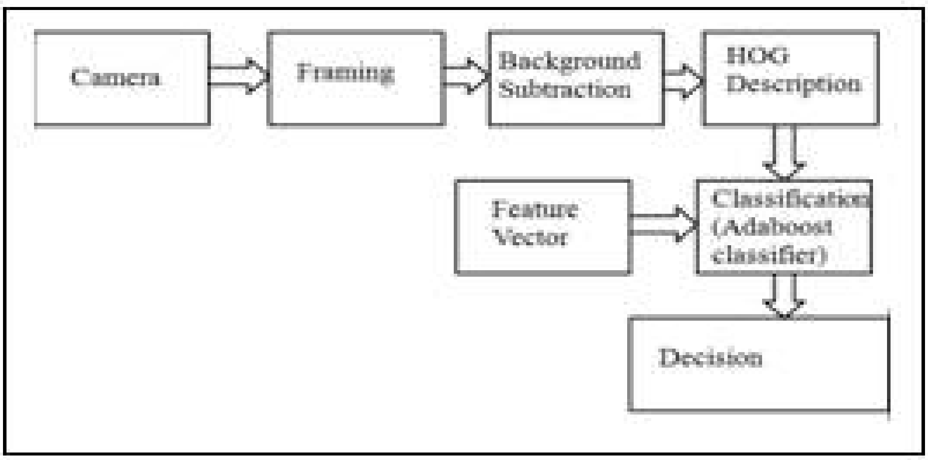

Fig.2. Block Diagram Of Proposed System

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering
(An ISO 3297: 2007 Certified Organization)
Website: www.ijircce.com
Vol. 5, Issue 6, June 2017

The description of block diagram is given below:
A) Background Substraction
Background subtraction, also known as Foreground Detection, is a technique in the fields of image processing and computer vision wherein an image's foreground is extracted for further processing (object recognition etc.). Generally an image's regions of interest are objects (humans, cars, text etc.) in its foreground. After the stage of image preprocessing (which may include image demising, post processing like morphology etc.) object localization is required which may make use of this technique.
B) HOG Description
The histogram of oriented gradients (HOG) is a feature descriptor used in computer visionand image processingfor the purpose of object detection. The technique counts occurrences of gradient orientation in localized portions of an image. In this work they focused on pedestrian detection in static images.
C) Hog Based Extraction
To calculate the HOG descriptors of an image, the image is first divided into small regions and for each region histogram of gradient directions or edge orientations will be computed. Combination of all these histograms forms the descriptor at last.
HOG is calculated with the following steps
1. Compute image gradients of each pixel
2. Accumulate weighted votes into orientation bins.
3. Contrast normalization for each block
4. Collect HOGs for all blocks
In order to obtain appearance information from images, need to extract discriminative visual features as below
1) Visual Representation
The Histograms of Oriented Gradients (HOG) descriptor has shown promising results in vehicle and pedestrian detection [08]. We took this descriptor as the core of our vehicle and pedestrian visual representation. The goal of this task is to generate visual descriptors of areas of the image to be used in future stages to determine whether these areas contain an object of interest or not. We propose a sparse version of the HOG descriptor (S-HOG) that focuses on specific areas of an image patch. This allows us to reduce the common high-dimensional HOG descriptor [10]. Fig.3. illustrates some of the blocks we have selected to generate the descriptors for different object classes. These blocks correspond to meaningful regions of the object (e.g. head, shoulder and legs for pedestrians). HOGs are computed over these sparse blocks and concatenated to form S-HOG descriptors. To accelerate S-HOG feature computation, we followed an integral image scheme
2) Object Classification
Due to performance constraints, did not implement a visual-based moving object detection. Instead, we used the regions of interest (ROI) provided by lidar detection to focus on specific regions of the image. For each ROI, visual features are extracted, and a classifier is applied to decide if an object of interest is inside the ROI.
The choice of the classifier has a substantial impact on the resulting speed and quality. We implemented a boosting-based learning algorithm called discrete Adaboost [5].

D) AdaboostClassifier
Adaboost, short for "Adaptive Boosting", is a machine learning meta-algorithm formulated by Yoav Freund and Robert Schapire who won the Gödel Prize in 2003 for their work. It can be used in conjunction with many other types of learning algorithms to improve their performance. The output of the other learning algorithms ('weak learners') is combined into a weighted sum that represents the final output of the boosted classifier. Adaboost is adaptive in the sense that subsequent weak learners are tweaked in favour of those instances misclassified by previous classifiers.[10]

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 6, June 2017

IV. SYSTEM HARDWARE IMPLEMENTATION

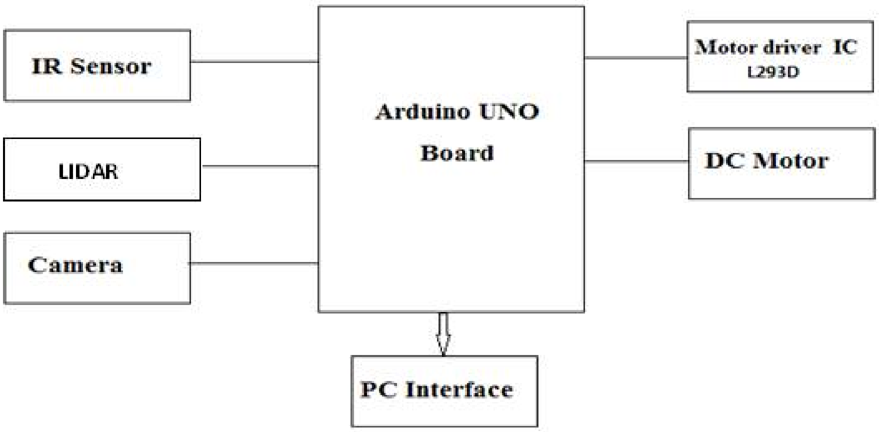

Fig.3.System Hardware Implementation

A) LIDAR Processing

LIDAR(Light Detection and Ranging), a new technology in the field of topographical data collection with high speed, high density and accurate data. LIDAR scanning can occur day or night;the main goal of the LiDAR processing is to get precise measurements of the shape of the moving obstacles in front of the vehicle.

B) IR Sensor

The first part of the object representation can be obtained bymeasuring the distance of the detected moving objects. The type of the object is deduce from the visible size of the object and follows a fixed fitting-model approach.

C) Camera Sensor

The camera-based classification produced several sub regions inside each ROI to cover many possible scale and size variations. Sometimes a ROI can contain more than one object of interest.

D) Applications

- Moving object recognition
- Activity Recognition
- Surveillances System
- Traffic management

V. CONCLUSION

The accurate detection and classification of moving objects is a important aspect. This system enhances the problem of intelligent vehicle perception. We have proposed the method that collect data as a key component, where active data as well as appearance data conisder an essential part in the location, arrangement and following of moving objects. We use a basic fundamental sensors to characterize, create and test the system approach : IR and camera. Coordinating class data at the identification level that allowto enhance the location by considering a proof over the different experiments.

REFERRENCES

[1]D. Santos and P. L. Correia, “Car recognition based on back lights and rear view features,” in Proc. IEEE Workshop Image Anal. Multimedia Interactive Serv., 2009, pp. 137-140

[2]R. O’Malley, M. Glavin, and E. Jones, “Vehicle detection at night based on taillight detection,” in Proc. Int. Symp.Veh.Comput. Syst., 2008, pp. 128-135

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 6, June 2017

[3]F. Garcia, P. Cerri, A. Broggi, A. Escalera, and J. M. Armingo, "Data fusion for overtaking vehicle detection based on radar and optical flow," in Proc. IEEE Intell.Veh.Symp., 2012, pp. 494-499..
[4]A. Haselhoff, A. Kummert, and G. Schneider, "Radar-vision fusion for vehicle detection by means of improved Haar-like feature and AdaBoost approach," in Proc. Eur. Signal Process. Conf., 2007, pp. 2070-2074.
[5]L. Huang and M. Barth, "Tightly-coupled LIDAR and computer vision integration for vehicle detection," in Proc. IEEE Intell.Veh.Symp., 2009, pp. 604-609.
[6]C. Premebida, G. Monteiro, U. Nunes, and P. Peixoto, "A LIDAR andvision-based approach for pedestrian and vehicle detection and tracking," in Proc. IEEE Intell. Transp. Syst. Conf., 2007, pp. 1044-1049.
[7]T.-D. Vu, "Vehicle perception: Localization, mapping with detection, classification and tracking of moving objects," Ph.D. thesis, Inst. Nat. Polytech. De Grenoble, Univ. Grenoble, Grenoble, France, 2009.
[8]Q. Baig, "Multisensor data fusion for detection and tracking of moving objects from a dynamic autonomous vehicle," Ph.D. dissertation, Lab. Inf. Grenoble, Univ. Grenoble, Grenoble, France, 2012.
[9]C.Wang, C. Thorpe, S. Thrun, M. Hebert, and H. Durrant-Whyte, "Simultaneous localization, mapping and moving object tracking," Int. J. Robot. Res., vol. 26, no. 9, pp. 889–916, Sep. 2007
[10]C. Mertz et al., "Moving object detection with laser scanners," J. FieldRobot., vol. 30, no. 1, pp. 17–43, Jan. 2013