

IJCAI-05

Proceedings of the Nineteenth International
Joint Conference on Artificial Intelligence

Edinburgh, Scotland
July 30–August 5, 2005

Sponsored by the
International Joint Conferences on Artificial Intelligence
Hosted by The British Computer Society Specialist Group on Artificial Intelligence
and the School of Informatics, The University of Edinburgh
In Partnership with the British Computer Society and Scottish Enterprise

Copyright © 2005 International Joint Conferences on Artificial Intelligence
All rights reserved.

Edited by Leslie Pack Kaelbling and Alessandro Saffiotti

Distributed by
Professional Book Center
P.O. Box 9249
Denver CO 80209
USA
800-848-6222
303-756-5222
www.gallup-house.com/professional.html

ISBN 0-938075-93-4

Printed in the United States

Design, composition, and manufacturing management by
Professional Book Center, Denver, Colorado

BRIEF CONTENTS

Dedication	iv
Past IJCAI Proceedings	iv
Foreword	v
IJCAI-05 Conference Organization	vi
Corporate Support	vi
Local Arrangements Committee	vii
Program Committee	vii
Poster Track Program Committee	viii
IJCAI-05 Awards	ix
Distinguished Papers	x
Invited Speakers	x
IJCAI Organization	xi
IJCAI-05 Reviewers	xii
Contents	
Case-based Reasoning	1
Constraint Satisfaction and Search	33
Knowledge Representation and Reasoning	349
Learning	633
Multi-Agent Systems	915
Natural Language	989
Philosophical Foundations	1173
Planning	1193
Uncertainty	1279
User Interface and Modeling	1405
Vision and Robotics	1431
Poster Papers	
AI and Cognitive Architecture	1503
Constraint Satisfaction and Search	1515
Knowledge Representation and Reasoning	1543
Learning and Information Extraction	1593
Multi-Agent Systems	1647
Natural Language and User Interfaces	1673
Planning	1707
Robotics and Perception	1723
Uncertainty	1747
Research Excellence Award	1763
Author Index	1776

PLANNING

- Mixed-Initiative Activity Planning for Mars Rovers
John Bresina, Ari Jónsson, Paul Morris,
and Kanna Rajan 1709
- Planning with graded fluents and actions
Marta Cialdea, Carla Limongelli, Andrea Orlandini,
and Valentina Poggioni 1711
- Automated Adaptive Support for Task and Information
Prioritizing
Tjerk de Greef, and Peter-Paul van Maanen. 1713
- Planning for Weakly-Coupled Partially Observable
Stochastic Games
AnYuan Guo and Victor Lesser. 1715
- Multi-Agent Assumption-Based Planning
Damien Pellier and Humbert Fiorino 1717
- Open-World Planning for Story Generation
Mark O. Riedl and R. Michael Young 1719
- Disjunctive Temporal Planning with Uncertainty
K. Brent Venable and Neil Yorke-Smith 1721

ROBOTICS AND PERCEPTION

- Talking Robots: a Fully Autonomous Implementation
of the Talking Heads
Jean-Christophe Baillie and Matthieu Nottale 1725
- An On-Line Time Warping Algorithm for Tracking
Musical Performances
Simon Dixon. 1727
- Path-Planning for Autonomous Training on Robot
Manipulators in Space
Froduald Kabanza, Roger Nkambou,
and Khaled Belghith 1729
- Growth of Motor Coordination in Early Robot Learning
M.H. Lee and Q. Meng. 1732
- Measuring the Cost of Robotic Communication
Avi Rosenfeld, Gal A Kaminka,
and Sarit Kraus 1734
- An Heuristic Search based Approach for Moving
Objects Tracking
Elena Sánchez-Nielsen
and Mario Hernández-Tejera. 1736

- 3-D Interpretation of Single Line Drawings
Kenji Shoji, Fubito Toyama,
and Juichi Miyamichi. 1738
- SVM-based Obstacles Recognition for Road Vehicle
Applications
M.A. Sotelo, J. Nuevo, D. Fernandez, I. Parra,
L.M. Bergasa, M. Ocana, and R. Flores 1740
- Detecting and locating faults in the control software of
autonomous mobile robots
Gerald Steinbauer and Franz Wotawa. 1742
- Learning discontinuities for switching between local
models
Marc Toussaint and Sethu Vijayakumar 1744

UNCERTAINTY

- Model minimization by linear PSR
Masoumeh T. Izadi and Doina Precup 1749
- Using core beliefs for point-based value iteration
Masoumeh T. Izadi, Ajit V. Rajwade,
and Doina Precup 1751
- Approximating Pseudo-Boolean Functions on
Non-Uniform Domains
R.F. Lax, Guoli Ding, Peter P. Chen,
and J. Chen 1754
- A Modal Logic for Reasoning about Possibilistic Belief
Fusion
Churn-Jung Liau and Tuan-Fang Fan 1756
- Networked Distributed POMDPs: A Synergy of
Distributed Constraint Optimization and POMDPs
Ranjit Nair, Pradeep Varakantham, Milind Tambe,
and Makoto Yokoo 1758
- Coping with exceptions in multiclass ILP problems
using possibilistic logic
Mathieu Serrurier and Henri Prade 1761

RESEARCH EXCELLENCE AWARD

- What kind of graphical model is the brain?
Geoffrey E. Hinton. 1765
- Author Index 1776

SVM-based Obstacles Recognition for Road Vehicle Applications

M. A. Sotelo, J. Nuevo, D. Fernandez, I. Parra, L. M. Bergasa, M. Ocana, R. Flores

Department of Electronics
University of Alcalá

Campus Universitario s/n Alcalá de Henares, Madrid, Spain
michael@depeca.uah.es

Abstract

This paper describes an obstacle Recognition System based on SVM and vision. The basic components of the detected objects are first located in the image and then combined with a SVM-based classifier. A distributed learning approach is proposed in order to better deal with objects variability, illumination conditions, partial occlusions and rotations. A large database containing thousands of object examples extracted from real road images has been created for learning purposes. We present and discuss the results achieved up to date.

1 Introduction

This paper describes an SVM-based object recognition system that can recognise both vehicles and pedestrians using vision. In our approach, the basic components of the objects are first located in the image and then combined with a SVM-based classifier. Our object detection technique is characterised by example-based learning algorithms. The salient features of a class are learnt by the system based on a set of examples. Example-based techniques have been previously used in natural, cluttered environments for pedestrian detection [Shashua, 2004]. In general, these techniques are easy to use with objects composed of distinct identifiable parts arranged in a well-defined configuration. This is the case of road vehicles, where a distributed learning approach based on components [Mohan, 2001] is more efficient for object recognition in real cluttered environments than holistic approaches [Papageorgiou, 2000]. Distributed learning techniques can deal with partial occlusions and are less sensitive to object rotations. The use of SVMs is a viable option as long as we intend to discriminate between two classes: car and non-car.

2 System Description

The system is divided in two modular subsystems. The first subsystem is responsible for vehicle detection and tracking. The second subsystem provides pedestrians detection using the information obtained by the vehicle detection module. In this paper, we focus on the vehicle recognition system alone, working with 320x240 monochrome images. The objects searching space is reduced by using the limits established by

the estimated lane markings. This helps reduce the rate of false positive detections. In case that no lane markings are detected, a basic area of interest is used instead covering the front part ahead of the host-vehicle. In a first stage, an attention mechanism has been devised with the intention of filtering out inappropriate candidate windows based on the lack of distinctive features, such as horizontal edges and symmetrical structures, which are essential characteristics of road vehicles. This has the positive effect of decreasing both the total computation time and the rate of false positive detections. Each road lane is sequentially scanned, from the bottom to the horizon line of the image, looking for collections of horizontal edges that might represent a potential obstacle. We use a distributed learning approach in which each individual part of the vehicle is independently learnt by a specialized classifier in a first learning stage. The local parts are then integrated by another classifier in a second learning stage. We have considered a total of 3 different sub-regions for each candidate region, covering the most characteristic parts of the vehicle. Two small sub-regions have been located in the area of the region where the wheels are supposed to be. A third sub-region is located in the central part of the region, covering the area where car plates and rear windshield are usually placed. The locations of the three sub-regions have been chosen in an attempt to detect coherent and structural car features. A set of features must be extracted from each sub-region and fed to the classifier. Before doing that, the entire candidate region of interest is pre-processed using a Canny operator in order to enhance the differential information contained in it (edges). The Canny image provides a good representation of the discriminating features of the car class. On the one hand, edges, both horizontal and vertical, are clearly visible and distinguishable. On the other hand, the vertical symmetry of a car remains unchanged. In addition, edges are not affected by colours or intensity. This property makes the use of edges robust enough to different car models of the same type. The pre-processed sub-region is directly applied to the input of the classifier. The dimensions of the entire region of interest are normalized before being fed to the classifier. A size of 70x80 pixels has been chosen, as it is adequate for detecting vehicles at long distances (up to 80 meters).

The global training strategy is carried out in two stages. In a first stage, separate SVM-based classifiers are trained using individual training sets that represent a subset of a sub-region.

This stage provides classification of individual parts of the candidate sub-regions. In a second step, the outputs of all classifiers are merged in a single SVM classifier in order to provide the final classification result.

3 Results

The system was implemented on a Apple PC at 2.0 GHz running the Debian GNU/Linux Operating System. The complete algorithm runs at 25 frames/s. We created a preliminary database containing 2000 samples of road vehicles. The samples were extracted from recorded images acquired in real experiments onboard a road vehicle in real traffic conditions in Madrid. Two different training sets were built for the same sub-region in different conditions in order to decrease the complexity of the training process. This yields a total of 6 training sets (2x3). All training sets were created at day time conditions using the TsetBuilder [Nuevo, 2005] tool, specifically developed in this work for this purpose. By using the TsetBuilder tool different candidate regions are manually selected in the image on a frame-by-frame basis. This allows to select candidate regions containing vehicles of different size, from different manufacturers, and so on. The number of non-vehicle samples in the training sets was chosen to be similar to the number of vehicle samples. We obtained a detection rate of 85% in a test set containing 1000 images, and a false detection rate of 5%. No image from the training set was used in the test set. As an example, figure 1 shows a sequence of images in which a vehicle is detected and tracked along the lane of the host vehicle. A blue box is overprinted over the detected vehicle indicating the estimated distance measured from the host vehicle. Other vehicles appearing along the adjoining lane are marked with a horizontal red line.

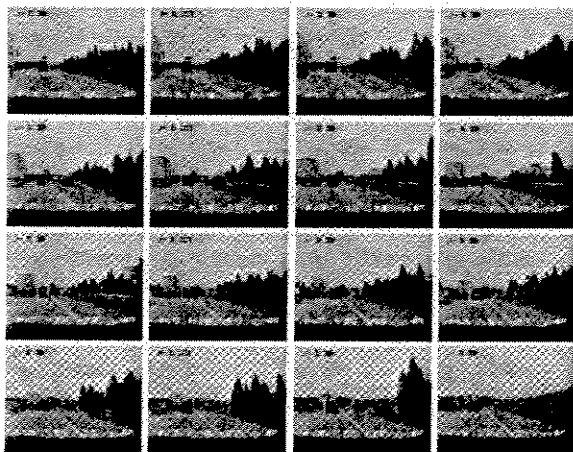


Figure 1: Vehicle detection and tracking in a sequence.

4 Conclusions and Future Work

We have developed a visual multi-frame two-stage object classification system based on Support Vector Machines

(SVM) [Boser, 1992]. The learning process has been simplified by decomposing the candidate regions into 3 local sub-regions that are easily learned by individual SVM classifiers. Several training sets have been built for each sub-region in order to cope with different weather and illumination conditions. The results achieved up to date using a set of 2000 samples are encouraging. Nevertheless they still need to be improved before being safely used as an assistance driving system onboard road vehicles in real conditions. For this purpose, the content of the training sets will be largely increased by including new and more complex samples that will boost the classifier performance. In addition, the attention mechanism will be refined in order to provide more candidates around the original candidate region. This will reduce the number of candidate regions that only contain a part of the vehicle, i.e., those cases in which the entire vehicle is not completely visible in the candidate region due to a misdetection of the attention mechanism.

Acknowledgment

This work has been funded by Research Projects CICYT DPI2002-04064-05-04 and FOM2002-002 (Ministerio de Fomento, Spain).

References

- [Shashua, 2004] A. Shashua, Y. Gdalyahu, and G. Hayu. Pedestrian detection for driving assistance systems: single-frame classification and system level performance. *Proceedings of the IEEE Intelligent Vehicles Symposium*, pages 1–6, Parma, Italy, June 2004.
- [Mohan, 2001] A. Mohan, C. Papageorgiou, and T. Poggio. Example-based object detection in images by components. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 23, April 2001.
- [Papageorgiou, 2000] C. Papageorgiou and T. Poggio. A trainable system for object detection. *International Journal of Computer Vision*, 38,1:15–33, 2000.
- [Boser, 1992] B. Boser, I. Guyon, and V. Vapnik. A training algorithm for optimal margin classifiers. *Proceedings of the Fifth Annual Workshop on Computational Learning*, 1992.
- [Nuevo, 2005] J. Nuevo. TsetBuilder User Manual. *Technical Report*. University of Alcala. <ftp://www.depeca.uah.es/pub/vision/SVM/manual.pdf>, 2005.