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# Contextual bayesian inference for visual object tracking and abnormal behavior detection

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# Contextual Bayesian Inference for Visual Object Tracking and Abnormal Behavior Detection

A thesis submitted in fulfilment of the  
requirements for the award of the degree

Doctor of Philosophy

from

THE UNIVERSITY OF WOLLONGONG

by

Philippe Loïc Marie Bouttefroy  
Masters of Engineering Studies  
(Telecommunications and Computer Science),  
Diplôme d'ingénieur

SCHOOL OF ELECTRICAL, COMPUTER  
AND TELECOMMUNICATIONS ENGINEERING  
2010

To my hair †

# Abstract

Visual object tracking has been extensively investigated in the last two decades for its attractiveness and profitability. It remains an active area of research because of the lack of a satisfactory holistic tracking system that can deal with intrinsic and extrinsic distortions. Illumination variations, oclusions, noise and errors in object matching and classification are only a fraction of the problems currently encountered in visual object tracking. The work developed in this thesis integrates contextual information in a Bayesian framework for object tracking and abnormal behavior detection; more precisely, it focuses on the intrinsic characteristics of video signals in conjunction with object behavior to improve tracking outcomes.

The representation of probability density functions is essential for modeling stochastic variables. In particular, parametric modeling is convenient since it makes possible the efficient storage of the representation and the simulation of the underlying stochastic process. The Gaussian mixture model is employed in this thesis to represent the pixel color distribution for segregation of foreground from background. The model adapts quickly to fast changes in illumination and resolves the problem of “pixel saturation” experienced by some existing background subtraction algorithms. The technique leads to better accuracy in the extraction of the foreground for higher-level tasks such as motion estimation.

The solution of the Bayesian inference problem for Markov chains and, in particular, the well-known Kalman and particle filters is also investigated. The integration of contextual inference is of paramount importance in the aforementioned estimators;

---

it results in object-specific tracking solutions with improved robustness. The vehicle tracking problem is explored in detail. The projective transformation, imposed by the environment configuration, is integrated into the Kalman and particle filters, which yields the “projective Kalman filter” and the “projective particle filter”. Extensive experimental results are presented, which demonstrate that the projective Kalman and particle filters improve tracking robustness by reducing tracking drift and errors in the estimated trajectory. The constraint on the known nature of the environment is then relaxed to allow general tracking of pedestrians. A mixture of Gaussian Markov random fields is introduced to learn patterns of motion and model contextual information with particle filtering. Such inference results in an increased tracking robustness to occlusions.

The local modeling with the Markov random fields also provides inference on abnormal behavior detection. Since local patterns are unveiled by the Markov random field mixture, detecting abnormal behavior is reduced to the matching of an object feature vector to the underlying local distribution, whereas the global approach, introducing generalization errors, involves complex, cumbersome and inaccurate decisions. Experimental evaluation on synthetic and real data show superior results in abnormal behavior detection for driving under the influence of alcohol and pedestrians crossing highways.

# Résumé

Le suivi d'objets visuel a été un domaine de recherche intense durant ces deux dernières décennies pour son attrait scientifique et sa rentabilité. Il reste un sujet de recherche ouvert de par le manque de système de suivi holistique satisfaisant, prenant en compte les distorsions intrinsèques et extrinsèques. Variations d'éclairement, occlusions, bruits et erreurs dans la correspondance et la classification d'objets ne sont qu'une partie des problèmes actuellement rencontrés en suivi d'objets. Le travail développé dans cette thèse intègre l'information contextuelle dans le cadre Bayésien pour le suivi d'objets et la détection de comportements anormaux. Plus précisément, la recherche porte sur les caractéristiques intrinsèques du signal vidéo en conjonction avec le comportement d'objets dans le but d'améliorer les résultats du suivi.

La représentation de fonctions de densité de probabilité est cruciale pour modéliser les variables aléatoires. En particulier, les modèles paramétriques sont pratiques puisqu'ils permettent un stockage compact de la représentation ainsi que la simulation du processus aléatoire sous-jacent. La mixture de Gaussiennes est utilisée dans cette thèse pour représenter la distribution de couleur d'un pixel dans le but de séparer l'avant-plan de l'arrière-plan. Le modèle s'adapte aux changements rapides d'éclaircissements et résout le problème de "saturation de pixels" rencontré avec certains algorithmes de soustraction d'arrière-plan. Il résulte de cette technique une meilleure précision lors de l'extraction de l'avant-plan pour des tâches de plus haut niveau telles que l'estimation du mouvement.

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La solution au problème d'inférence Bayésienne pour les chaînes de Markov, et en particulier, les filtres de Kalman et particulaire, est étudiée. L'intégration d'une inférence contextuelle dans ces estimateurs est primordiale pour améliorer le suivi d'objet. Il en découle des solutions propres à un contexte spécifique. Le problème de suivi de véhicules est également exploré en détails dans cette thèse. La transformation projective, imposée par la configuration de l'environnement, est intégrée dans les filtres de Kalman et particulaire, engendrant le "filtre de Kalman projectif" et le "filtre particulaire projectif". Des résultats expérimentaux exhaustifs sont présentés pour démontrer l'amélioration de la robustesse au suivi par les filtres de Kalman et particulaire projectifs. L'amélioration est caractérisée par la réduction de la dérive du suiveur et la réduction de l'erreur dans l'estimée de la trajectoire. La contrainte sur le caractère connu de l'environnement est ensuite supprimée pour permettre le suivi de piétons. Une mixture de champs aléatoires de Markov Gaussiens est introduite dans l'objectif d'apprendre les motifs de mouvements et de modéliser l'information contextuelle pour le filtrage particulaire. Une augmentation de la robustesse du suivi sous occlusion résulte d'une telle inférence.

La modélisation locale avec les champs aléatoires de Markov fournit également une inférence pour la détection de comportements anormaux. Puisque les motifs locaux sont révélés par la mixture de champs aléatoires de Markov, la détection de comportements anormaux est réduite à l'étude de la correspondance entre le vecteur de caractéristiques et la distribution locale sous-jacente. L'approche globale, quant à elle, introduit des erreurs de généralisation et implique des décisions complexes, peu élégantes et imprécises. L'évaluation expérimentale de la méthode proposée sur des données synthétiques et réelles présente des résultats supérieurs pour la détection des comportements anormaux de conducteurs en état d'ébriété et de piétons traversant les autoroutes.

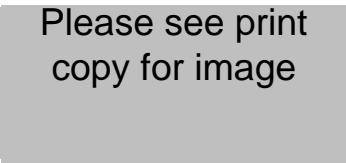


# Statement of Originality

This is to certify that the work described in this thesis is entirely my own, except where due reference is made in the text.

No work in this thesis has been submitted for a degree to any other university or institution, to the exception of the University Paris 13 (France) with which a cotutelle agreement (Joint Doctorate) has been signed.

Signed



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Philippe Loïc Marie Bouttefroy

21<sup>st</sup> of January, 2010

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# Contents

<b>1 Preliminaries</b>	<b>1</b>
1.1 Introduction . . . . .	1
1.2 Representation of Video Signals . . . . .	2
1.2.1 Concepts and Notation . . . . .	2
1.2.2 Video Acquisition . . . . .	4
1.2.3 Information Distortion . . . . .	5
1.2.4 Research Motivation and Assumptions . . . . .	8
1.3 Contributions of the Thesis . . . . .	9
1.4 Publications . . . . .	11
<b>2 Roadmap for the Object Tracking Maze</b>	<b>13</b>
2.1 Introduction . . . . .	13
2.2 Object Modeling . . . . .	14
2.2.1 Parametric Representations . . . . .	15
2.2.2 Non-parametric Representations . . . . .	18
2.2.3 Object Features . . . . .	20
2.2.4 Summary of Object Modeling . . . . .	24
2.3 Object Identification . . . . .	25

---

2.3.1	Object Detection using Supervised Learning . . . . .	25
2.3.2	Distribution Representation for Object Detection . . . . .	28
2.3.3	Object Segmentation . . . . .	32
2.3.4	Summary of Object Identification . . . . .	36
2.4	Object Tracking . . . . .	36
2.4.1	Deterministic Tracking . . . . .	37
2.4.2	Probabilistic Tracking . . . . .	39
2.4.3	Occlusion Handling . . . . .	44
2.4.4	Summary of Object Tracking . . . . .	46
<b>3</b>	<b>Semi-Constrained Gaussian Mixture Model for Background Sub- traction</b> . . . . .	<b>49</b>
3.1	Introduction . . . . .	49
3.2	Density Representation with Gaussian Mixture Model . . . . .	50
3.3	Background Modeling using the Gaussian Mixture Model . . . . .	52
3.3.1	Background/Foreground Classification . . . . .	56
3.3.2	State of the Art and Current Shortcomings . . . . .	57
3.3.3	Analysis of Background Subtraction with GMM . . . . .	58
3.4	Semi-Constrained Gaussian Mixture Model . . . . .	64
3.4.1	Mean Variable Learning Rate . . . . .	65
3.4.2	Standard Deviation Learning Rate . . . . .	66
3.4.3	Performance Analysis on Synthetic Data . . . . .	67
3.5	Experiment Results . . . . .	70
3.5.1	Experimental Setup . . . . .	70
3.5.2	Controlled Environment . . . . .	72
3.5.3	Natural Changes in Illumination . . . . .	78

---

3.6	Summary of the GMM for Background Modeling . . . . .	80
<b>4</b>	<b>Projective Kalman Filter for Vehicle Tracking</b>	<b>83</b>
4.1	Introduction . . . . .	83
4.2	Constraining the Tracking with the Environment . . . . .	84
4.2.1	Motivations . . . . .	85
4.2.2	Linear Fractional Transformation . . . . .	86
4.3	The Kalman Filter . . . . .	89
4.3.1	Closed-form Solution to the Bayesian Problem . . . . .	90
4.3.2	The Extended Kalman Filter . . . . .	91
4.3.3	The Unscented Kalman Filter . . . . .	92
4.4	Projective Kalman Filter . . . . .	93
4.4.1	State and Observation Updates . . . . .	95
4.4.2	The Mean-shift Procedure . . . . .	96
4.4.3	Extended versus Unscented Kalman Filter . . . . .	97
4.5	Vehicle Tracking System . . . . .	98
4.5.1	Tracker Initialization and Pruning . . . . .	101
4.5.2	PKF Initialization and Vehicle Detection . . . . .	101
4.6	Performance Analysis on Vehicle Tracking . . . . .	103
4.6.1	Experimental Setup and Data . . . . .	103
4.6.2	Comparison of the PKF and the EKF . . . . .	105
4.6.3	Effects of the Frame Rate on Tracking . . . . .	106
4.6.4	Mean-shift Convergence Speed at Low Frame Rates . . . . .	108
4.7	Summary of the Projective Kalman Filter . . . . .	111
<b>5</b>	<b>Projective Particle Filter for Vehicle Tracking</b>	<b>113</b>

---

5.1	Introduction . . . . .	113
5.2	Sequential Monte Carlo and Particle Filtering . . . . .	114
5.2.1	A Sub-optimal Bayesian Solution: The Particle Filter . . . . .	116
5.2.2	Samples Degeneracy and Resampling . . . . .	118
5.2.3	Particle Filter Summary . . . . .	119
5.3	Projective Particle Filter . . . . .	120
5.3.1	Importance Density and Prior . . . . .	120
5.3.2	Likelihood Estimation . . . . .	122
5.3.3	System Implementation . . . . .	123
5.4	Experiments and Results . . . . .	124
5.4.1	Mean Square Error Performance . . . . .	125
5.4.2	Importance Sampling Evaluation . . . . .	128
5.4.3	Tracking Performance and Discussion . . . . .	128
5.5	Summary of the Projective Particle Filter . . . . .	130
<b>6</b>	<b>Tracking Through Occlusion with Markov Random Fields</b>	<b>131</b>
6.1	Introduction . . . . .	131
6.2	Integration of Contextual Information . . . . .	132
6.2.1	Occlusion Handling . . . . .	132
6.2.2	Importance of Contextual Information . . . . .	133
6.2.3	Markov Random Fields . . . . .	134
6.3	Gaussian Markov Random Field Mixture . . . . .	137
6.3.1	Learning and Posterior Diffusion for Sparse Random Fields . . . . .	139
6.3.2	Simulated Annealing . . . . .	141
6.3.3	MRF Parameters Update . . . . .	141
6.4	Performance Analysis and Discussion . . . . .	142

---

6.4.1	Object Tracking System Implementation . . . . .	142
6.4.2	Experimental Procedure . . . . .	143
6.4.3	Mean Square Error Analysis . . . . .	145
6.4.4	Performance with Total Spatio-temporal Occlusion . . . . .	146
6.4.5	When Will the Algorithm Fail? . . . . .	147
6.5	Summary of Tracking Through Occlusion . . . . .	148
<b>7</b>	<b>Abnormal Behavior Detection with Markov Random Fields</b>	<b>153</b>
7.1	Introduction . . . . .	153
7.2	Abnormal Behavior Modeling . . . . .	154
7.3	Related Work . . . . .	156
7.3.1	Object Descriptor Extraction . . . . .	156
7.3.2	Activity Modeling . . . . .	157
7.3.3	Complexity Reduction . . . . .	158
7.3.4	Behavior Classification . . . . .	158
7.4	Modeling Behavior with MRFs . . . . .	159
7.4.1	Feature Vector Dimensionality Reduction . . . . .	159
7.4.2	Integration of Contextual Information in the MRF . . . . .	161
7.4.3	Stochastic Clustering Algorithm . . . . .	162
7.5	Analysis of the Stochastic Learning Algorithm . . . . .	164
7.5.1	Experimental Setup . . . . .	164
7.5.2	Distance Measure Selection . . . . .	166
7.5.3	Performance Analysis . . . . .	171
7.6	Abnormal Behavior Detection on Highways . . . . .	174
7.6.1	Experimental Setup . . . . .	174
7.6.2	Performance Analysis . . . . .	175



7.6.3 Discussion . . . . .	178
7.7 Summary of Abnormal Behavior Detection . . . . .	180
<b>8 Conclusions and Future Research</b>	<b>183</b>
8.1 Thesis Summary . . . . .	184
8.2 Suggestions for Improvements and Future Research . . . . .	186
<b>Bibliography</b>	<b>189</b>

# List of Figures

1.1	Video formation process . . . . .	2
1.2	Video structure and representation . . . . .	3
1.3	Scene projection and distortion . . . . .	4
1.4	Fixed camera versus moving camera . . . . .	6
1.5	Displays of an original video and its compressed version . . . . .	7
1.6	Histogram representations of the spatial and temporal noise . . . . .	7
2.1	Functional diagram of visual object tracking . . . . .	14
2.2	Example of rectangular and elliptic shapes . . . . .	16
2.3	Non-parametric representations of a person . . . . .	18
2.4	Profile of the 1D and 2D Laplacian of Gaussians. . . . .	22
2.5	Maximization of the distance between two hyperplanes . . . . .	27
2.6	Color histogram representation . . . . .	29
2.7	Representation of the hidden Markov chain model . . . . .	40
2.8	Three different types of occlusion . . . . .	45
3.1	Pixel probability density represented by a mixture model . . . . .	53
3.2	Original and foreground segmentation with saturated zone . . . . .	60
3.3	Display of the pixel saturation phenomenon . . . . .	61

---

3.4	Percentage of saturated pixels in a video sequence . . . . .	61
3.5	Background adaptation time for a new mixture component . . . . .	64
3.6	Performance on synthetic data . . . . .	68
3.7	Estimated mean to true mean MSE . . . . .	69
3.8	Number of foreground pixels under illumination changes . . . . .	73
3.9	Foreground segmentation of the <i>HighwayII</i> video sequence . . . . .	74
3.10	Foreground segmentation of the <i>People_Walking_1</i> video . . . . .	75
3.11	Foreground segmentation for office scenes . . . . .	77
3.12	Foreground segmentation in outdoor environment . . . . .	79
3.13	Foreground segmentation in indoor environment . . . . .	81
4.1	Examples of vehicle trajectories . . . . .	86
4.2	Vehicle projection on the camera plane . . . . .	87
4.3	Background subtraction on a low definition image . . . . .	96
4.4	Contribution of the Hessian matrix $\mathcal{H}_h$ . . . . .	99
4.5	Pixel position mean square error for EKF and UKF . . . . .	100
4.6	Overview of the vehicle tracking algorithm with PKF . . . . .	101
4.7	Example of tracking in dense vehicle flow . . . . .	102
4.8	Sequence showing the drift of a tracker . . . . .	106
4.9	Comparison of the and the proposed tracking algorithm . . . . .	107
4.10	Effects of the frame rate on the tracking performances . . . . .	107
4.11	Tracking rate for the PKF and the EKF . . . . .	109
4.12	Tracking robustness in low frame rate . . . . .	110
4.13	Mean-shift iterations for PKF and the EKF . . . . .	111
5.1	Example of vehicle track for PKF and standard filter . . . . .	125

5.2	Alignment of calculated and extracted trajectories . . . . .	126
5.3	Position mean square error <i>vs.</i> number of particles . . . . .	127
5.4	Position mean square error for 5 ground truth labeled vehicles . . . . .	127
5.5	Position mean square error without resampling step . . . . .	129
5.6	Drift tracking rate for projective and standard particle filters . . . . .	129
6.1	Representation of vehicle motion by local mixture of Gaussians . . . . .	135
6.2	Examples of neighborhoods in a graph. . . . .	136
6.3	Examples of cliques for the 8-neighborhood . . . . .	136
6.4	MRFs update with integration and with diffusion . . . . .	140
6.5	GMRFMPF and CONDENSATION tracking rates . . . . .	145
6.6	Tracking with GMRFMPF and CONDENSATION through occlusion	149
6.7	Examples of pedestrian tracking through occlusion . . . . .	150
6.8	Examples of vehicle tracking through occlusion (case A) . . . . .	151
6.9	Examples of vehicle tracking through occlusion (case B) . . . . .	152
7.1	Example of marginal densities of a feature vector . . . . .	160
7.2	Example of generated vehicle tracks . . . . .	165
7.3	ROC curves for ABD based on distance . . . . .	167
7.4	ROC curves for ABD based on local density $p(r \Theta)$ . . . . .	168
7.5	ROC curves for ABD based on Mahalanobis distance measure . . . . .	170
7.6	ROC curves of stochastic learning algorithm for ABD . . . . .	171
7.7	ROC curves for the proposed technique and the SOM. . . . .	173
7.8	Examples of abnormal behavior on highways. . . . .	175
7.9	ROC curve for ABD on highway . . . . .	176
7.10	Abnormal behavior detection rendering on real data . . . . .	178

# List of Tables

3.1	GMM Parameter Initializing Values . . . . .	71
4.1	Vehicle Tracking Dataset . . . . .	104
4.2	Vehicle Tracking System and PKF Parameter Initializing Values . . .	105
5.1	Linear Fractional Transformation Parameters . . . . .	125
5.2	MSE for the Standard and the Projective Particle Filters . . . . .	126
6.1	GMRFM Particle Filter Parameter Initializing Values . . . . .	144
6.2	Comparison of the MSE for GMRFMPF and CONDENSATION . . .	146
6.3	Recovery Rate Under Occlusion . . . . .	146
7.1	Correct ABD Rate with MRFs . . . . .	173
7.2	Correct ABD Rate versus Size of SOM . . . . .	174
7.3	Correct ABD Rate on the Video Dataset . . . . .	177

# List of Algorithms

3.1	Generic Gaussian Mixture Algorithm . . . . .	55
4.1	Generic Projective Kalman Filter Algorithm . . . . .	100
5.1	Resampling Algorithm . . . . .	119
5.2	Projective Particle Filter Algorithm . . . . .	123
6.1	GMRFM Particle Filter Algorithm . . . . .	143

# Nomenclature

ABD Abnormal Behavior Detection

ADABOOST Adaptive Boosting

ANN Artificial Neural Network

AVC Advanced Video Coding

BAC Breath Alcohol Content

CCD Charge-Coupled Device

CMOS Complementary Metal Oxide Semiconductor

CONDENSATION Conditional Density Propagation

DCT Discrete Cosine Transform

DUI Driving Under the Influence

DWT Discrete Wavelet Transform

EKF Extended Kalman Filter

EM Expectation-Maximization

EPF Extended Particle Filter

GMM Gaussian Mixture Model

GMPHDF Gaussian Mixture Probability Hypothesis Density Filter

GMRF Gaussian Markov Random Field

GMRFM Gaussian Markov Random Field Mixture

GMRFMFPF Gaussian Markov Random Field Mixture Particle Filter

HMM Hidden Markov Model

JPDAF Joint Probability Data Association Filter

LOG Laplacian Of Gaussians

MAP Maximum A Posteriori

MCM Motion Correspondence Matrix

ML Maximum Likelihood

MLP Multi Layer Perceptron

MMSE Minimum Mean Square Error

MPDA Merged Probabilistic Data Association

MPEG Moving Picture Experts Group

MRF Markov Random Field

MSE Mean Square Error

OOP Object-Oriented Programming

PCA Principle Component Analysis

PCNSA Principal Component Null Space Analysis

pdf probability density function

PF Particle Filter

PHD Probability Hypothesis Density

PKF Projective Kalman Filter

PPF Projective Particle Filter

ROC Receiver Operating Characteristic

SIR Sampling Importance Resampling

SIS Sequential Importance Sampling

SOM Self Organizing Map

SSD Sum of Squared Differences

SVD Singular Value Decomposition

SVM Support Vector Machine



UKF Unscented Kalman Filter

UPF Unscented Particle Filter

UT Unscented Transform

WB White Balance