

Background Modeling and Foreground Detection for Video Surveillance

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Dedication

Background modeling has a long and well published history since it was commonly adopted as a means for object detection and tracking in video at the end of the last century. In the decade and a half since, there have been thousands of researchers and nearly 10,000 publications that have either contributed novel approaches or employed existing approaches in new computer vision and machine learning applications.

On behalf of the authors, I would like to dedicate this book to all the researchers who have contributed their experiences and understanding to this field. In particular, I would like to recognize researchers who have gone beyond explaining their algorithms to provide intuition and a greater understanding of the myriad approaches to background modeling. These researchers have impacted the field with their intuitive papers, comprehensive evaluations, landmark data sets, workshops, working groups, and books in background modeling. They have reduced redundancy and helped mature this field by conveying not just what they did, but also what they learned from their hundreds to thousands of hours toiling with videos. This book is intended as one such contribution, by bringing together a background modeling overview, history, applications, practical implementations, and evaluation practices in one resource. We hope you find it useful.

Christopher Stauffer, Ph.D.

on behalf of T. Bouwmans, F. Porikli, B. Höferlin, and A. Vacavant

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Preface

Background modeling and foreground detection are important steps in the video processing field such as video-surveillance, optical motion capture, multimedia applications, teleconferencing and human-computer interface. Conventional background modeling methods exploit the temporal variation of each pixel to model the background while foreground detection applies change detection. The last decade witnessed very significant publications in this field and recently new applications in which background is not static, such as recordings taken from mobile devices or Internet videos, generate new developments to detect robustly moving objects in challenging environments. Thus, effective methods for robustness to deal both with dynamic backgrounds, illumination changes which occur in real-life scene with fixed cameras or mobile devices have been recently developed and so different strategies are used such as automatic feature selection, model selection or hierarchical models. Another feature of background modeling methods is that the use of advanced models has to be computed in real-time and low memory requirements. Algorithms have to be designed to meet these requirements.

In this context, this handbook solicited contributions to address this wide range of challenges met in background modeling and foreground detection for video-surveillance. Thus, it groups the works of the leading teams in this field over the recent years. By incorporating both existing and new ideas, this handbook gives a complete overview of the concepts, theories, algorithms, and applications related to background modeling and foreground detection. First, an introduction to background modeling and foreground detection for beginners is provided by surveying statistical models, clustering models, neural networks and fuzzy model. Furthermore, leading methods and algorithms for detecting moving objects in video surveillance are presented. A description of recent complete datasets and codes are given. Moreover, an accompanying website¹ is provided. This website contains the list of chapters, their abstracts and links to some software demonstrations. It allows the reader to have quick access to the main resources, datasets and codes in the field. Finally, with this handbook, we aim to bring a one-stop solution, *i.e.*, access to a number of different models, algorithms, implementations and benchmarking techniques in a single volume. The handbook consists of five parts.

Part I presents a comprehensive introduction to background modeling and foreground detection for video surveillance systems. Chapter 1 and Chapter 2 provide a first complete survey of the traditional and recent background models with a classification of them following the mathematical models used. Furthermore, these chapters present the available resources such as datasets and implementations, and thus facilitate comparison and evaluation of background subtraction algorithms. We provide an accompanying web site: the Background Subtraction Web Site². This website contains a full list of the references in the field, links to available datasets and codes. In each case, the list is regularly updated and classified according to the sections of these chapters. Chapter 3 provides a first valuable overview of different background initialization strategies. An initial background model

¹<http://sites.google.com/site/backgroundmodeling/>

²<http://sites.google.com/site/backgroundsubtraction/Home>

that describes the scene without foreground objects is the prerequisite in video-surveillance. Chapter 4 investigates background subtraction in the case of moving cameras. Indeed, most of today's videos are captured from moving platforms. Traditional background subtraction algorithms are not applicable for the moving-camera case. There have been some extensions of background subtraction algorithms to deal with mobile cameras where cameras motion is known or scene geometry is restricted, such as stationary mounted pan-tilt-zoom cameras. So, the authors review these extensions and present an effective solution for the case of videos captured from an online moving camera.

Part II concerns representative traditional and recent models. Chapter 5 gives a detailed overview of the statistical models. Chapter 6 describes a non-parametric method for background modeling/foreground detection in videos, specifically the well-known Pixel-Based Adaptive Segmenter (PBAS). The authors provide a detailed explanation of PBAS, as well as further optimization for the various parameters involved. Furthermore, PBAS is evaluated within a thorough experimental evaluation on the standard Change Detection dataset, including the assessment of how the choices of values for various parameters affect performance. Chapter 7 presents another famous background model named ViBe. ViBe achieved a fast initialization technique and a novel updating mechanism by introducing a memoryless update policy and spatial diffusion. The authors also discuss some improvements such as the distinction between the segmentation map and the updating mask, or a controlled diffusion mechanism. Concerning the computational cost, the notion of background subtraction complexity factor is introduced to express the speed of the algorithm, and show that ViBe has a low complexity factor to achieve real-time performance. Chapter 8 develops online learning models based on a stochastic approximation, which have an inherent robustness and low computational complexity. One of them models the background with a multivariate Gaussian distribution, while the other uses a probabilistic self-organizing map. Both of them associate a uniform distribution to the foreground to cope with any incoming objects adequately. Experimental results show that stochastic approximation methods perform well both in qualitative and quantitative terms when compared with a selection of state of the art algorithms. Chapter 9 presents group sparsity based methods for background and foreground separation and develops an algorithm called LRGS based on the group sparsity notion which is capable of handling video sequences recorded by both stationary and moving cameras. LRGS operates on matrices of tracked point trajectories and decomposes them into foreground and background trajectories by enforcing a low-rank constraint on the background matrix and applying a l_0 -norm penalty to the l_2 -norm of the rows (trajectories) of the foreground matrix thus encouraging row wise sparsity. The method is evaluated on both the synthetic data and several real videos and compared to other algorithms for trajectory labeling. Chapter 10 presents a robust detection through a rough set theory framework. Furthermore, an integrated 3D histon is proposed, where the histon distribution is calculated by considering the color value on three channels jointly. By determining the extent of similarity using Gaussian membership function, 3D fuzzy histon is subsequently used to compute 3D Fuzzy histon roughness index (3D FHRI). Foreground detection in a video sequence is performed by evaluating the Bhattacharyya distance between the model roughness index distribution and the roughness index distribution computed in the current frame in three types of histons (basic histon, 3D histon, and 3D fuzzy histon).

Part III focuses on several video-surveillance dynamic backgrounds and illumination changes. Chapter 11 introduces two efficient approaches for foreground detection and tracking for automated visual surveillance. One of them uses a non-parametric density estimation, while the other uses a single class background pixel model with Support Vector Regression (SVR). The density estimation is achieved either through an Adaptive Kernel

Density Estimation (AKDE) algorithm with a training phase to learn the kernel covariance and the foreground/background decision threshold per pixel or a Recursive Modeling (RM) algorithm with fixed per pixel memory requirements. For SVR, the Support Vector Data Descriptions (SVDD) are determined in the training phase and are used to calculate the radius of the hyper sphere that serves as the decision boundary during the classification stage. The SVR based background pixel modeling is augmented with a target tracking framework that handles multiple targets using size, color, motion and shape histogram information. For detecting moving objects in video sequences, Chapter 12 develops a novel approach based on a Beta-Liouville distribution, extended to the infinite case, and learned by means of incremental variational Bayes. This model is learned via variational Bayesian inference which is an efficient deterministic alternative to purely Bayesian inference. This method is robust and adaptive to dynamic background, and it has the ability to handle multi-modal background distributions. Moreover, thanks to the nature of non-parametric Bayesian models, the determination of the correct number of components is sidestepped by assuming that there are an infinite number of components. The results demonstrate the robustness of this approach in the presence of dynamic backgrounds on several real video surveillance sequences. Chapter 13 investigates three spatio-temporal background models for moving object detection. The first one is a combinational background model in which a statistical, a local feature-based and an extrapolation-based background models are combined adaptively. The second one is an integrated background model based on the feature SLDP where a statistical framework is applied to an illumination-invariant feature. The third one is an integrated background model StSIC realized by considering a similarity of intensity changes among pixels. Each background model uses a spatio-temporal feature to tackle various background changes robustly. The combinational model is suitable for close-up and low contrast scenes, and SLDP and StSIC are suitable for the scenes where illumination and dynamic changes affect the same region at the same time. Maritime environment represents a challenging application due to the complexity of the observed scene (waves on the water surface, boat wakes, weather issues). In this context, Chapter 14 presents a method for creating a discretization of an unknown distribution that can model highly dynamic background such as water background with varying light and weather conditions. A quantitative evaluation carried out on the recent MAR datasets demonstrates the effectiveness of this approach. Chapter 15 describes a spatial-color mixture of Gaussians based on a hierarchical scene model. It combines a global spatial modeling with a temporal pixel modeling of the scene which takes into account the spatial consistency between pixels. Global models permit to describe the whole scene, both background and foreground areas. The target model is dynamically created during the detection process, allowing for a better background/foreground separation and provides data information of a higher level than pixel. This may help a tracking step by introducing a natural combination between the detection and the tracking module. The detection results show that this approach outperforms several traditional methods under difficult conditions. Chapter 16 presents the Grassmannian Robust Adaptive Subspace Tracking Algorithm (GRASTA), an online algorithm for robust subspace tracking, and its variant t-GRASTA that incorporates geometric transforms on the data. For GRASTA, the authors use a low-rank model for data that may be corrupted by outliers and have missing data values. For t-GRASTA, a low-rank model for misaligned images that may be corrupted by outliers is proposed. Both GRASTA and t-GRASTA use the natural l_1 -norm cost function for data corrupted by sparse outliers, and both perform incremental gradient descent on the Grassmannian, the manifold of all d -dimensional subspaces for fixed d . The two algorithms operate only one data vector at a time, making them faster than other state-of-the-art algorithms and suitable for streaming and real-time applications.

Part IV addresses sensors, hardware and implementations issues. Chapter 17 presents an overview of ubiquitous imaging sensors for presence detection. The main technologies considered are regular visible light cameras, thermal cameras, depth cameras and radar. The technologies are described, their operating principles explained and the performance analyzed. Chapter 18 presents a framework that is able to accurately segment foreground objects with RGB-D cameras. In particular, more reliable compact segmentations are obtained in the case of camouflage in color or depth. Chapter 19 details a GPU implementation of jointly modeling a scene background and separating the foreground. The authors propose a way of modeling that does not assume that background pixels are Gaussian random variables. They also incorporate an interesting periphery detector or a detector for short-term motion. Finally, a GPU implementation of this method provides a significant speed increase over the CPU implementation. Chapter 20 presents a GPU implementation for background-foreground-separation via Robust PCA and Robust Subspace Tracking. Starting with a brief introduction to some basic concepts of manifold optimization, the Robust PCA problem in the manifold context is discussed as well as the cost functions and how their optimization can practically be performed in batch and online mode. In order to keep the discussion close to real-world applications, pROST which performs online background subtraction on video sequences is presented. Its implementation on a graphics processing unit (GPU) achieves real-time performance at a resolution of 160×120 pixels. Experimental results show that the method succeeds in a variety of challenges such as camera jitter and dynamic backgrounds. Chapter 21 concerns two background subtraction methods for embedded hardware. Thus, the authors detail two FPGA architectures which is based on the Horprasert method, with a shadow detection extension, and the other one is based on the Codebook method. In each case, the architecture developed on reconfigurable hardware is explained and the performance is experimentally assessed. Chapter 22 presents a resource-efficient background modeling and foreground detection algorithm that is highly robust to illumination changes and dynamic backgrounds (swaying trees, water fountains, strong wind and rain). Compared to many traditional methods, the memory requirement for the data saved for each pixel is very small in the proposed algorithm. Moreover, the number of memory accesses and instructions are adaptive, and are decreased even more depending on the amount of activity in the scene and on a pixel's history. Furthermore, the authors present a feedback method to increase the energy efficiency of the foreground object detection even further. This way, foreground detection is performed in smaller regions as opposed to the entire frame. The feedback method significantly reduces the processing time of a frame. Finally, a detailed comparison of the feedback method and the sequential approach in terms of processing times and energy consumption is provided.

Part V covers the resources and datasets required for evaluation and comparison of background subtraction algorithms. Chapter 23 proposes the BGSLibrary which provides an easy-to-use C++ framework together with a couple of tools to perform background subtraction. First released in March 2012, the library provides 32 background subtraction algorithms. The source code is platform independent and available under the open source GNU GPL v3 license, thus the library is free for non-commercial use. The BGSLibrary also provides a Java based GUI (Graphical User Interface) allowing the users to configure the input video-source, regions of interest, and the parameters of each BS algorithm. Chapter 24 gives an overview of the most cited motion detection methods and datasets used for their evaluation. Then, the authors provide benchmarking results on different categories of videos, for different methods, different features and different post-processing methods. Thus, the chapter provides the reader with a broad overview on the most effective methods available today on different types of videos. All benchmark results are obtained on the changedetection.net dataset. Chapter 25 presents the Background Models Challenge

(BMC), which is a benchmark based on a set of both synthetic and real videos, together with several performance evaluation criteria. Finally this chapter presents the most recent results obtained by the BMC, such as the final ranking obtained in very first challenge. Finally, possible evolutions for this benchmark, according to recent advances in background subtraction and its potential applications are discussed.

The handbook is intended to be a reference for researchers and developers in industries, as well as graduate students, interested in background modeling and foreground detection applied to video surveillance and other related areas, such as optical motion capture, multimedia applications, teleconferencing, video editing and human-computer interfaces. It can be also suggested as reading text for teaching graduate courses in subjects such as computer vision, image processing, real-time architecture, machine learning and data mining.

The editors of this handbook would like to acknowledge with their sincere gratitude the contributors for their valuable chapters and the reviewers for the helpful comments concerning the chapters in this handbook. We also acknowledge the reviewers of the original handbook proposal. Furthermore, we are very grateful for the help that we have received from Sarah Chow, Marsha Pronin and others at CRC Press during the preparation of this handbook. Finally, we would like to acknowledge Shashi Kumar from Cenveo for his valuable support about the LaTeX issues.

About the Editors

Thierry Bouwmans (<http://sites.google.com/site/thierrybouwmans/>) is an Associate Professor at the University of La Rochelle, France. His research interests consist mainly in the detection of moving objects in challenging environments. He has recently authored 30 papers in the field of background modeling and foreground detection. These papers investigated particularly the use of fuzzy concepts, discriminative subspace learning models and robust PCA. They also develop surveys on mathematical tools used in the field. He has supervised Ph.D. students in this field. He is the creator and the administrator of the Background Subtraction Web Site. He has served as a reviewer for numerous international conferences and journals.

Benjamin Höferlin (<http://www.vis.uni-stuttgart.de/nc/institut/mitarbeiter/benjamin-hoeferlin.html>) received his M.Sc. degree and his Ph.D. degree in Computer Science from the University of Stuttgart, Germany (2013). He is currently associated with the Biologically Oriented Computer Vision Group, Institute of Cognitive Science, Osnabrück University, Germany. His research interests include computer vision, automated video analysis and visual analytics of video data. He is the author of the "Stuttgart Artificial Background Subtraction Dataset" (SABS) that allows precise challenge-based evaluation of background modeling techniques.

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Antoine Vacavant (<http://isit.u-clermont1.fr/~anvacava>) obtained his Master's degree from the University Lyon 1, France, in 2005, and the Ph.D. degree in computer science from the University Lyon 2 in 2008. He is now associate professor at the University of Auvergne Clermont Ferrand 1. Head of the professional bachelor in 3D imaging, he gives lectures of image rendering, software engineering and object/event based programming in the IUT of Le Puy en Velay. Member of the ISIT lab, UMR 6284 UdA/CNRS / research team CaVITI, his main research topics are discrete and computational geometry, image analysis and computer vision. He has organized the first BMC (Background Models Challenge) at ACCV 2012, which addresses the evaluation of background subtraction algorithms thanks to a complete benchmark composed of real and synthetic videos.

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