Video Processing and Understanding Lab

TEC2011-25995 EventVideo (2012-2014)

Strategies for Object Segmentation, Detection and Tracking in Complex Environments for Event Detection in Video Surveillance and Monitoring

D5.3v1

EVENTVIDEO TEST SEQUENCES, GROUND-TRUTH AND EVALUATION METHODOLOGY

Video Processing and Understanding Lab
Escuela Politécnica Superior
Universidad Autónoma de Madrid

Supported by GOBIERNO DE ESPAÑA MINISTERIO DE ECONOMÍA Y COMPETITIVIDAD

AUTHOR LIST

Álvaro García Martin	Alvaro.Garcia@uam.es
José M. Martínez	JoseM.Martinez@uam.es
Juan C. SanMiguel	JuanCarlos.Sanmiguel@uam.es

CHANGE LOG

Version	Date	Editor	Description
0.0	18/06/2012	Juan C. SanMiguel	Initial version
0.1	22/06/2012	Álvaro García Martín	Video object segmentation and People modeling and detection (datasets and evaluation methodology with ground-truth)
0.2	25/06/2012	Juan C. SanMiguel	Evaluation methodology without ground-truth Final revision
1.0	28/06/2012	José M. Martínez	Version 1

CONTENTS:

1. Introduction

1.1. Motivation

During the past years, automatic video surveillance systems have experienced a great development driven by the need of security in private and public places. Many approaches are available whose effectiveness is not clear [1]. They have to deal with a huge variety of environments that might change over time (e.g., lighting conditions) or present a substantial difference (e.g., sunny or rainy day). Hence, the performance of such systems can degrade significantly in these situations [2].

To precisely identify which approaches operate better in certain situations or applications, performance evaluation has been proposed in the literature as a way to determine their strengths and weaknesses. The widely used empirical approach consists on the performance evaluation through the analysis of the obtained results. For such analysis, two main aspects have to be specified: the dataset (a set of sequences covering the situations that the algorithm might face being large enough to represent real world conditions) and the metrics to measure the precision of algorithms (which allow to quantify their performance). These two aspects are also known as the evaluation protocol [3][4].

Traditional performance evaluation approaches use metrics based on ground-truth information that represents a manual annotation of the ideal result. The generation of the ground truth is usually a time consuming step and, therefore, limits the amount of data in the dataset. Although there are other approaches not focused on ground-truth information [5][6], most of the current literature assumes the availability of such data. Furthermore, the existence of several metrics increases the complexity of designing an evaluation protocol. Another point to be taken into account is the increasing quantity of video data available, which generates a new need to automate and optimize the whole tracking evaluation process.

In this document, we focus on the main stages that compose a typical video surveillance system (addressed within the EventVideo project) and describe the evaluation scenarios of the EventVideo project. Then, we briefly review the material to be used for each stage: the test sequences, the ground-truth and the evaluation methodologies.

1.2. Document structure

This document contains the following chapters:

- Chapter 1: Introduction to this document

- Chapter 2: Overview of the evaluation scenarios proposed in the EventVideo project
- Chapter 3: Describes the available evaluation material for the main stages of video surveillance systems that are also studied in the EventVideo project
- Chapter 4: Defines the two evaluation methodologies used in the EventVideo project
- Chapter 5: Finish this document with some conclusions and future work.
- Chapter 6: Finish this document with some conclusions and future work.

2. Evaluation scenarios

2.1. Selected analysis stages

For the EventVideo project, we consider the typical stages that compose a video surveillance system (depicted in **Figure 1**). They are:

- *Video object segmentation*: It detects the moving objects in the scene by applying sequential analysis steps such as foreground analysis, noise filtering and shadow removal. The output of this stage is a binary mask indicating the foreground objects.

- *People modeling and detection*: The likelihood (score) of being people is computed for each candidate region (that could either a frame region or a blob extracted from the foreground binary mask). A person model has to be pre-computed and the task comprises to find the similarity of such model and the observed blobs. The output of this stage is a numerical value (score) for each analyzed candidate.

- *Video object tracking*: It consists on locating an object or objects of interest as they move in time throughout a scene by means of a vision device such as a camera. The output of such stage in the location of each tracked target (its position and size).

- *Event recognition*: It detects events using the information from the previous stages. An event is considered as an action performed by a person (e.g., interaction with objects, walking). The output of this stage includes a descriptor with the score (the likelihood of the event), the frame span and the location of the event.

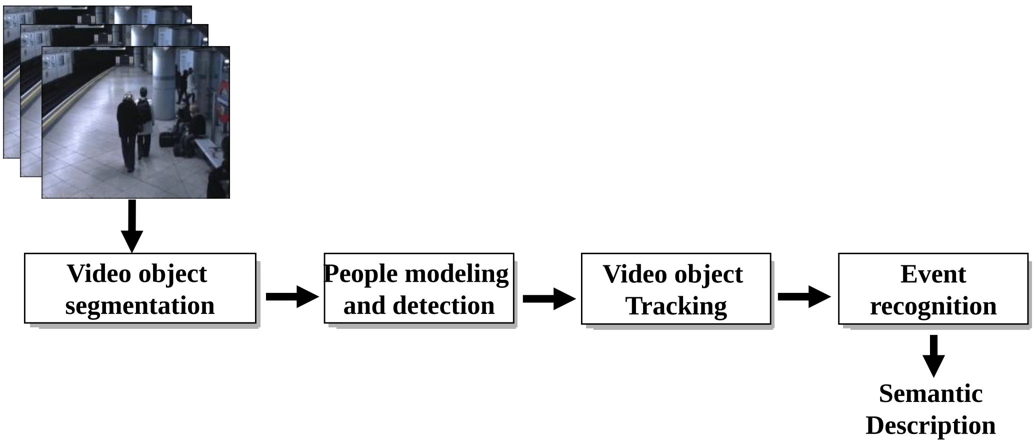


Figure 1 – Typical processing chain for a video surveillance system

2.2. Scenario classification

For the *EventVideo* project, the evaluation process considers different types of scenarios that represent the visual data obtained in real world conditions at different stages considered in the project (e.g., video object segmentation and tracking). For understanding the limitations of current approaches, each scenario is classified according to two criteria: complexity and density. The former describes if the visual data represents situations that can be easily characterized or not. For example, video object segmentation based on background subtraction can be easily performed when dealing with static cameras without moving background objects but the complexity highly increases when dealing with moving cameras or motion in the background. The latter describes a critical aspect in video surveillance: the number of moving objects (e.g., people) in the sequence. Independently of the problems being addressed, an increasing number of objects affect the performance of the system. This fact is particularly interesting in video surveillance as it is applied to crowded places such as airports, train stations and mass sport events. For example, the detection of abandoned objects presents variable difficulty depending on the number of moving objects in the scene (fewer people, less complexity). Finally, we consider two levels for each criterion: low and high. The two criteria and their values can be summarized as shown in Table 1. Sample frames are depicted in Figure 2.

Scenario	**Complexity**	**Density**
S1	Low	Low
S2	High	Low
S3	Low	High
S4	High	High

Table 1 – Proposed scenario classification in the EventVideo project

Figure 2 – Sample frames for proposed evaluation categories of the EventVideo project. (From top left to bottom right): recognition of simple events (standing) with few people, recognition of complex interactions with objects with few people, abandoned object detection in crowded environments and recognition of complex events (bag stealing) in crowded enviroments.

3. Evaluation material

For each analysis stage mentioned in section 2.1, we describe the available evaluation material based on visual information to be used within the EventVideo project

3.1. Video object segmentation

For video object segmentation, one dataset has been created by the VPULab focused on the main problems that affect motion-based algorithms for video-object segmentation. Moreover, an analysis of publicly available datasets is also provided in the appendix.

3.1.1. Chroma Video Segmentation Ground-truth – CVSG

The CVSG dataset [10] consists of a set of video scripts which have then been filmed according to a thorough review and classification of the critical factors that affect the behavior of segmentation algorithms. Foreground objects have been recorded in a chroma studio, in order to automatically obtain pixel-level high quality segmentation masks for each generated sequence. The resulting corpus contains the segmentation ground-truth plus filmed sequences mounted over different backgrounds. Table 2 summarizes the critical factors that have been considered. Since specific settings for these factors can significantly increase (high complexity settings) or decrease (low complexity settings) segmentation accuracy, they seem a convenient mechanism to regulate sequence complexity, allowing the generation of multiple complexity scenarios (only low-density S1-S2 scenarios, 14 sequences). We next describe these factors including a brief discussion on their influence on the overall sequence complexity.

Foreground (Objects)							**Background**		**Camera**
Single objects					Groups				
Textural complexity	Apparent velocity	Object structure	Uncovered extent	Object size	Frame largest velocity difference	Object interactions	Textural complexity	Multimodality	Motion scheme

Table 2 – Critical factors in motion-based object segmentation

Foreground critical factors

Moving objects properties significantly influencing segmentation accuracy have been divided into single-object and object-group properties. Within the first set we have included:

1. Textural complexity. Motion segmentation algorithms need to establish the amount of change within an area between two consecutive frames; the more distinctive spatial information is, the more reliable the estimation of this amount can be expected. Hence low complexity settings for this critical factor correspond to high textured objects, whereas color uniformity corresponds to higher complexity.

2. Apparent velocity. Since background normally presents instabilities and noise, too slow objects (which result in small temporal changes) are hard to discriminate. However, too fast ones require large search windows in motion estimation and tracking, thus degrading efficiency and normally also influencing accuracy, especially when optical flow is being derived from the motion compensation vectors available in coded sequences. Therefore, slow or fast objects correspond to high complexity settings, while complexity decreases the more similar are the velocities of the camera and the objects.

3. Object structure. Perfectly rigid objects obviously simplify segmentation when working with optical flow approaches. In situations in which this constraint is only verified piece-wise accuracy can be degraded if individual objects are to be extracted from the moving object masks or when handling object parts which might remain motionless whilst the whole object is globally undergoing a specific motion (e.g., the alternatively static feet of a walking person while the rest of the body is propelled forward). This latter case along with non-rigid objects undergoing a completely chaotic motion have been classified as high complexity. Simpler cases of piece-wise rigid objects will range from average to low complexity. Finally, rigid objects represent low complexity settings.

4. Uncovered extent. Uncovered parts of objects might seriously hamper motion estimation, due to the lack of region or points correspondence. This decreases accuracy in optical flow based techniques as well as in the tracking mechanisms involved in determining the temporal evolution of objects. Low complexity settings must therefore avoid situations leading to object uncovering, which should be included for higher complexity.

5. Object size. This factor must be only considered in the general case of a moving camera. In this case camera motion is normally derived from the frame dominant motion, which implicitly assumes that objects are smaller than the background area. Minimum object sizes are not a priori limited excepting the possible semantic constraints to remove background artifacts. Therefore low complexity settings would correspond to small objects and high complexity ones include those which dimensions are fairly comparable to the background area.

Regarding relevant properties concerning objects groups, the following critical factors have been identified:

1. Frame largest velocity difference. Large differences between the fastest and the slowest object simultaneously appearing within a frame can hinder the setting of a proper threshold to discriminate object motion when adaptive schemas are used. These schemas work without human supervision relying on a preliminary analysis on motion distribution. Normally it is assumed that bigger values of this distribution correspond to real objects, and thus adaptive thresholds might cause small moving objects to blend into the background. Hence, high complexity settings for this critical factor should include objects with very different velocities interacting together and low complexity settings must consider only objects with similar velocities.

2. Object interactions. These might influence motion estimation, but they do especially affect to the formation of individual objects within the foreground masks and to the tracking accuracy (i.e. the object temporal evolution). Therefore, they may be ignored when dealing with algorithms simply focused on extracting foreground masks. We can consider:

    a. Relative trajectories. When a number of objects have intersecting trajectories, object overlapping hampers individual object separation and objects can be lost after occlusion. Thereby intersecting objects must be exclusively used in high-complexity settings.

    b. Object split and merge. Object separation is hard to identify after two different objects merge and remain overlapped for a certain time, thus affecting object tracking. Additionally if individual object references are lost, further splits will require the creation of additional spatio-temporal objects, resulting in important degradations in objects being merged and split a number of times (e.g., any object successively used by several people). Thus, split and merge processes must also be included only in high-complexity settings.

Background critical factors

These factors mainly refer to background properties which might affect motion estimation:

1. Textural complexity. As aforementioned, temporal change can be derived with higher reliability within textured areas. In fact, low textured background areas remain apparently static under low camera motion, being thus very probably misclassified as objects. Consequently, scenarios including an important amount of uniform areas correspond to high-complexity, while entirely textured backgrounds correspond to low-complexity situations.

2. Multimodality. This refers to the property of some backgrounds to undergo small variations usually considered irrelevant from a semantic point of view (such as twinkling water, swaying trees or glowing flames). These backgrounds significantly hinder segmentation algorithms, thus defining high-complexity settings.

Camera motion critical factors

We here just consider the camera motion scheme. Camera motion influences the overall sequence and thereby plays a decisive role in segmentation accuracy. Static cameras, the simplest case, do not alter motion information, which results in low complexity sequences. Uniform camera motion can be robustly estimated and advantageously used during segmentation; we label these sequences as average complexity. Finally, high complexity corresponds to fast jerky camera motions, due to hand-held or uncalibrated video-cameras. In this case the small temporal duration of the involved patterns prevents from applying robust estimation procedures and its velocity is very likely to mask object motion.

Figure 3 – Sequence examples. Every row shows three random frames from a sequence.

3.2. People modelling and detection

For video people modeling and detection, one dataset has been created by the VPULab focused on the main problems that affect people detection in surveillance videos. Moreover, an analysis of publicly available datasets is also provided in the appendix.

3.2.1. Person Detection dataset - PDds

The PDds corpus or dataset [15] consists of a set of video and associated ground-truth, for the evaluation of people detection algorithms in surveillance video scenarios. Sequences from scenes with different levels of complexity have been manually annotated. Each person present at a scene has been labeled frame by frame, in order to automatically obtain a people detection ground-truth for each sequence. Sequences have been classified into different complexity categories depending on critical factors that typically affect the behavior of detection algorithms. The resulting corpus exceeds other public pedestrian datasets in the amount of video sequences and its complexity variability.

Table 3 summarizes the critical factors that have been considered in the video complexity classification and Table 4 summarizes the video sequences and complexity. Since specific settings for these factors can significantly increase (high complexity settings) or decrease (low complexity settings) segmentation accuracy, they seem a convenient mechanism to regulate sequence complexity, allowing the generation of multiple complexity scenarios (S1-S4 scenarios, 91 sequences). We next describe these factors including a brief discussion on their influence on the overall sequence complexity.

Background						**Classification**					
Textural complexity			Variability			Appearance variability			People/Object interactions		
Not textured	Slightly textured	Textured	Lighting changes	View changes	Multimodal	Pose variations	Different clothes	Carry objects	Objects	People	Objects & People

Table 3 – Critical factors on people detection video corpus

			Background		Classification	
Sequence	Category	Scenario	Textural complexity	Variability	Appearance variability	People/Object interactions
1-4	C1	S1	Low	Low	Low	Low
5-6	C1	S1	Low	Medium	Low	Low
7-8	C2	S1	Low	Low	Medium	Low
9-10	C2	S1	Low	Low	Medium	Medium
11-12	C2	S1	Low	Medium	Low	Medium
13	C3	S2	Medium	Medium	Medium	Low
14-16	C3	S2	Medium	Medium	Medium	Medium
17-18	C4	S2	Low	Low	Medium	High
19-20	C4	S2	Low	Low	High	Medium
21	C4	S2	Low	Low	High	High
22-24	C5	S2	Medium	High	Medium	High
25	C5	S2	Medium	High	High	Medium
26	C5	S3	High	High	Medium	High
27-33	C5	S3	High	High	High	Low
34-65	C5	S3	High	High	High	Medium
66-90	C5	S3	High	High	High	High

Table 4 –People detection video corpus

Background critical factors

We here define background complexity as the difficulty to detect in the scene the initial objects candidate to be person, due to the presence of edges, multiple textures, lighting changes, reflections, shadows and any kind of background variation. The following critical factors have been identified:

1. Textural complexity. Scenarios including an important amount of textured areas can make highly difficult the localization of initial object candidates. In fact, depending on the algorithm used, highly textured background areas can be easily wrongly detected as objects. Consequently, low textured background areas correspond to lower complexity situations and vice versa.

2. Variability. This refers to the property of some backgrounds to undergo variations usually produced by external factors (light and view point changes) or multimodal backgrounds (such as twinkling water, swaying trees or glowing flames). Static scenarios with less variations correspond with low complexity levels, while scenarios with multiple variations correspond with more challenging situations.

People classification critical factors

We here define it as the difficulty to verify the object candidates to be person in the scene. It is related to the number of objects, their velocity, partial occlusions, pose variations and interactions between different people and/or objects. We have grouped these elements into two fundamental critical factors:

1. Appearance variability. People appearance exhibits very high variability since they are non-rigid objects, they can change pose, they can also wear different clothes and carry different objects, they have a considerable range of sizes and shapes mainly due to the point of view and the relative situation with the camera. People with limited appearance variability (no pose changes, no sizes variations, etc) entail low complexity levels, while the cases with high appearance variability entail a more complex classification.

2. People/Object interactions. People must be identified in real-life scenarios, that is they must be detected in the context of the environment surrounding them. People present interactions with objects and/or with other people. These interactions make more difficult their identification and classification. In order to identify all persons involved in these situations, it is necessary to deal with occlusions. Occlusions resulting from objects, other persons or visibility of the camera limits the visible appearance of the person occluded.

Figure 4 – Sequence examples. Every row shows three random frames from a sequence.

3.3. Video Object tracking

For video object tracking, one dataset has been created by the VPULab focused on the main problems that affect video object tracking in surveillance videos. Moreover, an analysis of publicly available datasets is also provided in the appendix.

3.3.1. Single Object Video Tracking dataset- SOVTds

The selection of the test scenarios is one of the most important steps when developing an evaluation protocol. Each previously mentioned issue has to be represented in the dataset for achieving a correct understanding of the capabilities of the tracking algorithm. Moreover, different levels of complexity have to be covered in the test data. Hence, this dataset is designed with four complexity levels including both real and synthetic sequences. The addressed problems and the modeled situations are described as follows.

Selected tracking problems

Several problems have to be taken into account that corresponds to real-world situations. In the proposed dataset, we have modeled the following tracking-related problems:

1. Complex (fast) motion: The target changes its trajectory unexpectedly or increases its speed abruptly; the tracker might lose the target if it exceeds the search area.
2. Gradual (and global) illumination changes: In long sequences, the illumination might change due to weather conditions, time passing, etc. In this case, the target model might become outdated making harder the tracking task.
3. Abrupt (and local) illumination changes: As the target moves, it can enter in areas with different illumination. Hence, the tracker might be confused and lose the target.
4. Noise: It appears as random variations over the values of the image pixels and can significantly degrade the quality of the extracted features for the target model.
5. Occlusion: It is defined when an object moves between the camera and the target. It can be partial or total if, respectively, a region or the whole target is not visible.

Complexity factors

In the following table, we describe the criteria for defining the complexity factors of the test sequences

Problem	Criteria (factors)
Complex Movement	The target changes its speed (pixels/frame) abruptly in consecutive frames
Gradual Illumination	The average intensity of an area changes gradually with time until a maximum intensity difference is reached
Abrupt Illumination	The average intensity of an area changes abruptly with respect to its surroundings (maximum intensity difference)
Noise	It includes natural (snow) or white Gaussian noise which is manually added with varying deviation value
Occlusion	Objects in the scene occlude a percentage of the target
Scale Changes	The target changes its size with a maximum relative change regarding its original size.
Similar Objects	An object with similar color to the target appears in the neighborhood of the target

Table 5 –Complexity factors for the video tracking dataset

Modeled situations

As a tracker can operate in different conditions in which the same problem appears, we propose to organize them into four situations ranging from completely controlled (e.g., synthetic sequences) to uncontrolled (e.g., real-world sequences). Moreover, the complexity of the tracking problems is estimated for each sequence of the situations. They are:

1. Synthetic sequences (S1): It is composed of synthetic sequences that provide controlled testing conditions allowing to isolate each problem. They consist on a moving ellipse in a black background that can contain squares of the same or different color (acting as, respectively, similar or occlude objects). We have created sequences to model all the selected problems with five degrees of complexity for each one. In total, 35 sequences were generated with around 3500 frames. Sample frames are shown in the first row of Figure 5.

2. Laboratory sequences (S2): It provides a natural extension of the S1 situation by representing real test data in a laboratory setup under controlled conditions. An object with a simple color pattern was used for generating such data. We have recorded sequences to model all the selected problems with three complexity levels for each one. For some problems (complex movement, occlusion, scale changes and similar object problems), the sequences were recorded using the test object whereas for the other ones (noise, gradual and abrupt illumination changes), a single sequence was recorded without any problems and then, they were artificially included. In total, 21 sequences were generated with around 6500 frames. Sample frames are shown in the second row of Figure 5.

3. Simple real sequences (S3): It includes data from previously existing datasets that have been captured in noncontrolled conditions. We have extracted clips from the original sequences that contain isolated tracking problems. As each target has different characteristics [4], we have grouped the sequences into three target-dependent categories: cars (from MIT Traffic [16] and Karlsruhe [17] datasets), faces (from TRECVID2009 [18], CLEMSON[19] and VISOR [20] datasets) and people (from TRECVID2009 [18], i-Lids [21], PETS2009 [22], PETS2000 [22] and CAVIAR [23] datasets). For each target type and problem, three sequences with varying complexity level were composed making a total of 53 sequences with around 8500 frames. Sample frames are shown in the third row of Figure 5.

4. Complex real sequences (S4): The last situation contains the most complex sequences, which are clips from other datasets that include several problems. Once the algorithms are tested for each problem individually, it is a good idea to check the performance in more realistic (and complex) situations. Similarly to the previous situation, we also distinguish three problems have been estimated and classified according the defined criteria. All these sequences were extracted from the MIT Traffic [16] (for cars), CLEMSON [19] (for faces) and PETS2009 [22] (for people) datasets. In total, 15 sequences were selected with around 4500 frames. Sample frames are shown in the fourth row of Figure 5.

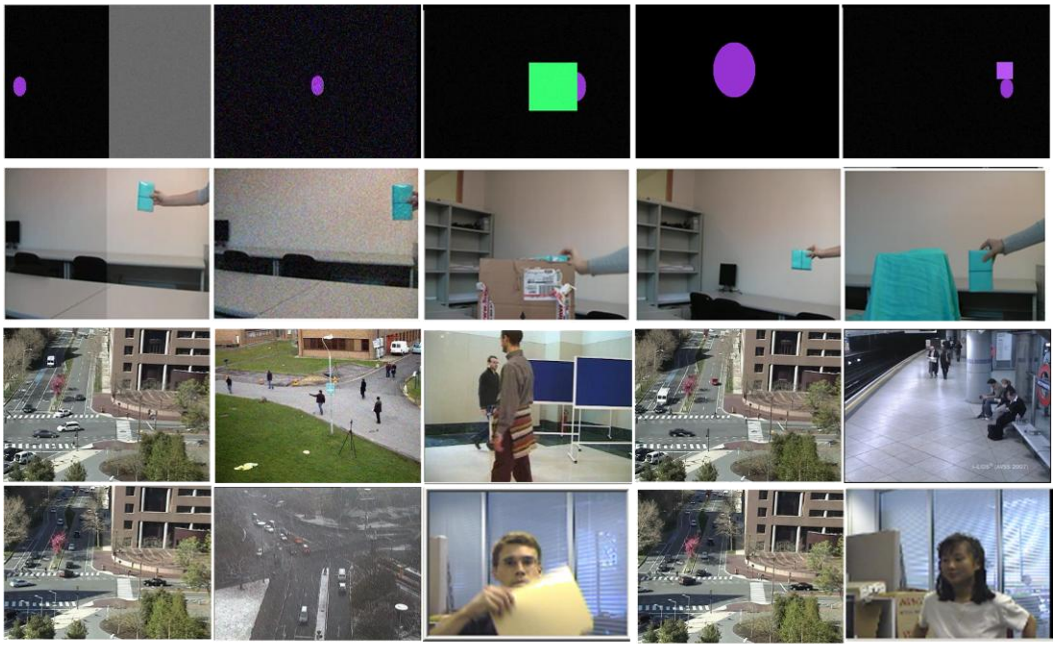


Figure 5 – Sample frames for the situations of the proposed dataset (from top row to bottom row): synthetic (S1), laboratory (S2), Simple real (S3) and Complex real (S4). In addition, samples of some tracking-related problems are also presented for each column (from left to right): abrupt illumination change, noise, occlusion, scale change and (color-based) similar objects.

3.4. Event detection

For event detection, two datasets have been created by the VPULab focused on the detection of abandoned/stolen objects and human-object interactions in controlled environments. Both datasets are described as follows:

3.4.1. Abandoned and Stolen Object Discrimination dataset - ASODds

The dataset [7] consists of two sets of annotations of the foreground binary masks of the abandoned and stolen objects. The first one has been obtained by manually annotating the objects of interest in the video sequence (annotated data). The second one represents real data has been obtained by running [8] over the test sequences to get inaccurate masks (real data). Figure 6 shows an example of such data.

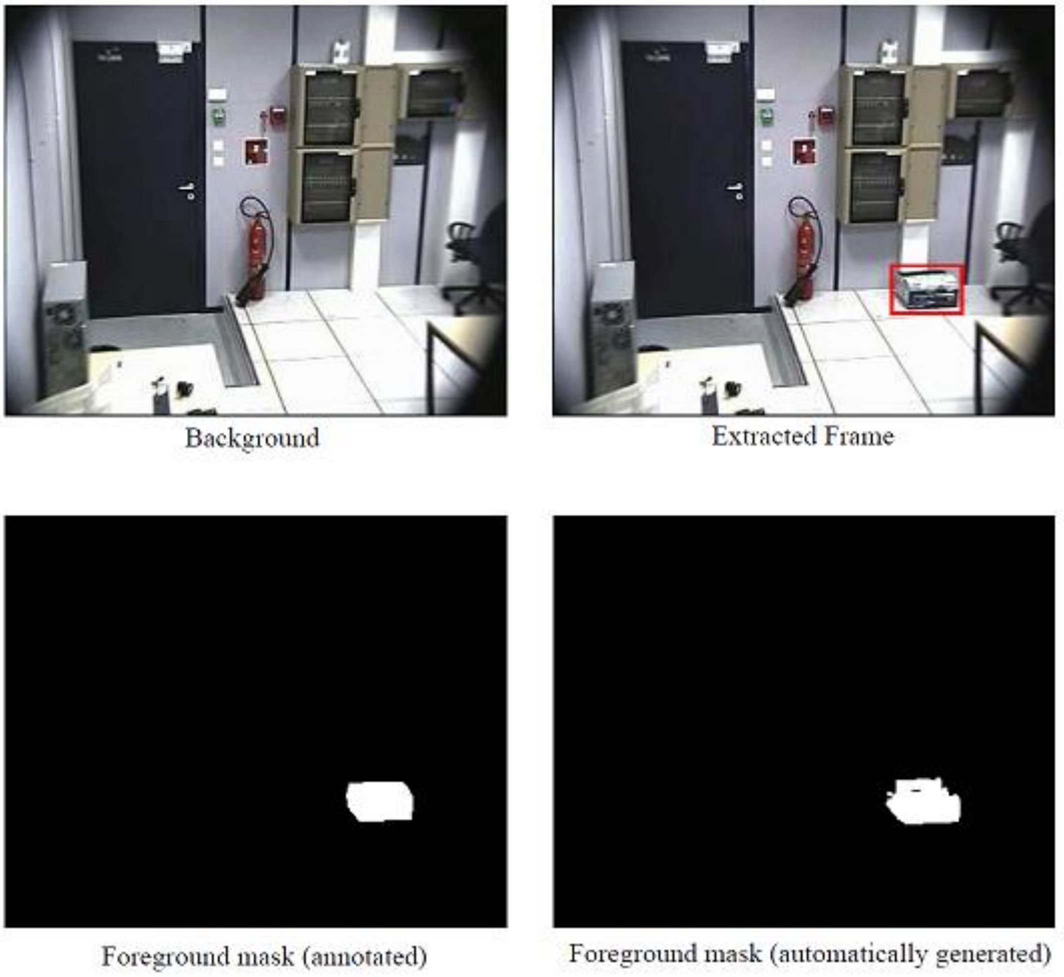
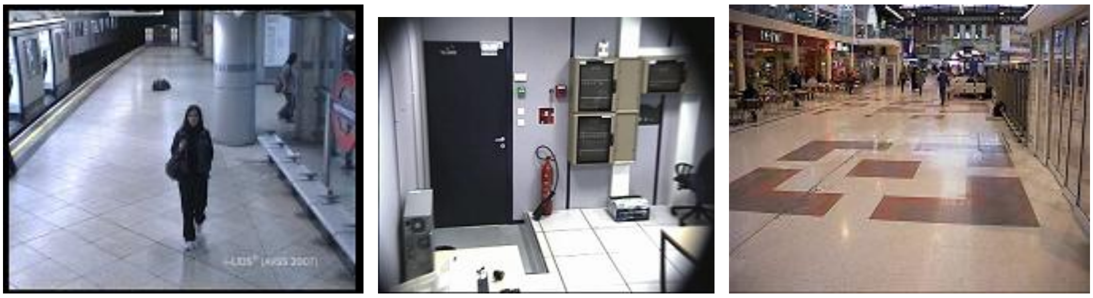


Figure 6 – Sample frames for the ASODds dataset and annotations (automatic and manual) of the object of interest

Then, we have grouped all the test sequences into three categories according to a subjective estimation of the background complexity that consists on the presence of edges, multiple textures, lighting changes, reflections, shadows and objects belonging to the background. Currently, three categories have been defined considering Low (C1), medium (C2) and High (C3) background complexity. According to the criteria proposed in section 2.2, the categories C1 and C2 present low complexity and few number of objects (situation S1) whereas the C3 covers low complex and crowded scenarios (situation S3). Sample frames of such categories are shown in Figure 7 and a summary of the annotated events in the dataset and the associated complexity of each category is available in Table 6.



Category 1 Category 2 Category 3

Figure 7 – Available categories in the ASODds dataset

Category	Number of annotations (blobs)				Complexity
	Annotated sequences		Real Sequences		
	Abandoned	Stolen	Abandoned	Stolen	
C1	771	442	756	863	Low
C2	666	316	794	397	Medium
C3	595	174	852	660	High
All	2032	932	2402	1920	

Table 6 – ASODds dataset description

3.4.2. Event Detection dataset – EDds

Currently, the dataset [9] contains 17 sequences taken using a stationary camera at resolution of 320x240 at 12 fps. The dataset is focused on two types of human-related events: interactions and activities. In particular, two activities (Hand Up and Walking) and three human-object interactions (Leave, Get and Use object) have been annotated.

We have grouped all the test sequences into three categories according to a subjective estimation of the analysis complexity considering:

- Foreground complexity (S1), defined as the complexity to extract the foreground due to the presence of edges, multiple textures, lighting changes, reflections, shadows and objects belonging to the background.

- Tracking complexity (S2), defined as the difficulty to track foreground blobs in the sequence. It mainly differentiates crowded from less-populated sequences.
- Feature complexity (S3), defined as the difficulty to classify moving and temporally stationary foreground in a scenario in order to extract/analyze relevant features.
- Event complexity (S4), defined as the difficulty to detect/recognize the annotated events in a scenario. It is related with the velocity of the event execution, the (partial) occlusion of the action performed and the variability in appearance of the actor.

Sample frames of such categories are shown in the following images:

Category 1 Category 2 Category 3

Figure 8 – Available categories in the EDds dataset

A summary of the annotated events in the dataset and the associated complexity of each category is available in the following table:

Sc.	Events Occurrences					Complexity Estimation			
	Interactions			Activities					
	LEA	GET	USE	HUP	WLK	S1	S2	S3	S4
1	18	13	9	9	54	M	L	M	M
2	7	7	10	14	44	M	M	M	H
3	14	14	22	20	10	V	H	V	V

Table 7 – EDds dataset description

The complexity estimation codes are Low (L), Medium (M), High (H) and Very High (V). The events are Leave-object (LEA), Get-object (GET), Use-object (USE), Hand Up (HUP) and Walking (WLK).

4. Evaluation methodology

According to [4], performance evaluation methodologies can be roughly divided into analytical and empirical methods. The former describes approaches that evaluate trackers by by considering their principles, their requirements and their complexity. Hence, it is not required to implement the algorithm under evaluation. However, this evaluation is difficult as algorithms may be complex composed of several stages. The latter reduce the complexity of the evaluation task by inspecting the results of the algorithm and deciding which performance level they have.

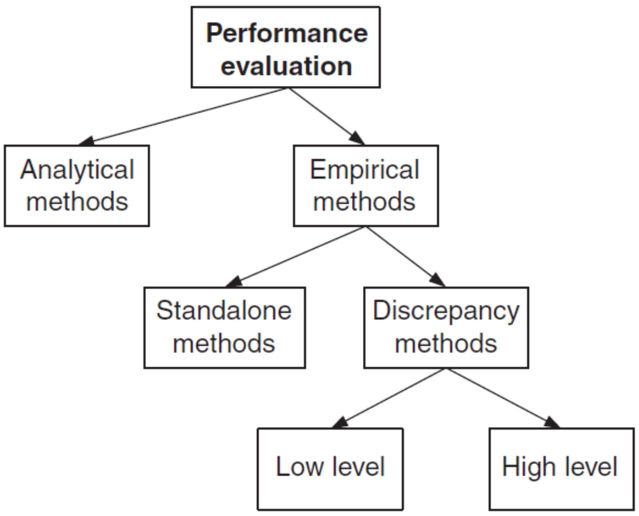


Figure 9 – Performance evaluation methodologies [4].

In the EventVideo project, the empirical methods are used for evaluating the stages of the video surveillance system. Among them, we distinguish between standalone and discrepancy methods. Both are employed in the project and they are described as follows.

4.1. Based on ground-truth data

Common tracking performance evaluations use empirical discrepancy methods [4] that compare off-line ground-truth data with the estimated target state. Ground-truth data are expensive to produce and therefore usually cover only small temporal segments of test video sequences and represent only a small percentage of data variability. This limitation makes it difficult to extrapolate the performance evaluation results to (unlabeled) new sequences. Moreover, the evaluation using ground truth is not feasible for on-line performance analysis [5].

4.1.1. Video object segmentation

The metrics most commonly used in literature are those based on ground-truth pixel level evaluation:

- True positive (TP): The number of pixels correctly classified as foreground (pixel value 1).
- True negative (TN): The number of pixels correctly classified as background (pixel value 0).
- False positive (FP): The number of pixels incorrectly classified as foreground.
- False negative (FN): The number of pixels incorrectly classified as background.

Let us define an experiment from P positive instances and N negative instances. The four outcomes can be formulated in a 2×2 contingency table or confusion matrix, as follows:

		Ground Truth		
		p	n	**Total**
Prediction	p’	TP	FP	P’
	n’	FN	TN	N’
	Total	P	N	

Table 8 – True positives, true negatives, false positives and false negatives

These measures are often combined in the state of the art object segmentation. These measures are:

- Precision: It is defined as the total number of pixels correctly classified as foreground/ background vs the total number of pixels correctly or incorrectly classified as foreground/ background.

$$\boldsymbol{Precision}\,(pixels\_of\_value\_0) = P0 = \frac{TN}{TN + FN} \qquad (4.1)$$

$$\boldsymbol{Precision}\,(pixels\_of\_value\_1) = P1 = \frac{TP}{TP + FP} \qquad (4.2)$$

- Recall: It is defined as the total number of pixels correctly classified as foreground/ background vs the total real (ground truth) number of pixels of foreground/ background.

$$\boldsymbol{Recall}\,(pixels\_of\_value\_0) = R0 = \frac{TN}{TN + FP} \qquad (4.3)$$

$$\boldsymbol{Recall}\,(pixels\_of\_value\_1) = R1 = \frac{TP}{TP + FN} \qquad (4.4)$$

- Fscore: A measure that combines precision and recall is the harmonic mean of precision and recall, the traditional F-measure or balanced F-score.

$$\boldsymbol{Fscore}\,(pixels\_of\_value\_0) = FS0 = \frac{2 \cdot P0 \cdot R0}{P0 + R0} \qquad (4.5)$$

$$\boldsymbol{Fscore}\,(pixels\_of\_value\_1) = FS1 = \frac{2 \cdot P1 \cdot R1}{P1 + R1} \qquad (4.6)$$

In order to achieve the objective of evaluating and finding the optimal parameters of the algorithms, it have been weighted equivalently the detection of foreground/background (ones and zeros) merging the above measures through the sum (although it could have used any other function). The optimal parameter selection and evaluation is performed by choosing the maximum sum:

$$SUM = FS0 + FS1 \qquad (4.7)$$

4.1.2. People modeling and detection

In order to evaluate different people detection approaches, we need to quantify the different performance results. In the state of the art, performance can be evaluated at two levels: sequence sub-unit (frame, window, etc) or global sequence. Sub-unit performance is usually measured in terms of Detection Error Tradeoff (DET) [33][34] or Receiver Operating Characteristics (ROC) [35][36] curves. Global sequence performance is usually measured in terms of Precision-Recall (PR) curves [37][38][39]. The first level gives us information of the classification stage, while the second one provides overall system performance information. In order to evaluate a video surveillance system, it is more interesting to compare the overall performance. In both cases the detectors output is a confidence score for each person detection, where larger values indicate higher confidence. Both evaluation methods compute progressively the respective parameters such as the number of false positives, Recall rate or Precision rate from the lowest possible score to the highest possible score. Each score threshold iteration provides a point on the curve.

ROC curves represent the fraction of true positives out of the positives (true positive rate, TPR, Recall or Sensitivity) vs. the fraction of false positives out of the negatives (false positive rate, FPR or 1-Specificity). We aim to evaluate and compare the overall performance of different detection systems, so we have chosen the second evaluation method. For each value of the detection confidence, Precision-Recall curves compute Precision and Recall as follows:

$$\boldsymbol{Precision} = \frac{\#TruePositivePeopleDetections}{\#TruePositivePeopleDetections + \#FalsePositivePeopleDetections} \qquad (4.8)$$

$$\textbf{\textit{Recall}} = \frac{\#TruePositivePeopleDetections}{\#TruePositivePeopleDetections + \#FalseNegativePeopleDetections} \quad (4.9)$$

In order to evaluate not only the yes/no detection decision but also the precise pedestrians locations and extents, we use three evaluation criteria, defined by [40], that allow comparing hypotheses at different scales: the relative distance, cover, and overlap. The relative distance dr measures the distance between the bounding box centers in relation to the size of the annotated bounding box. Cover and overlap measure how much of the annotated bounding box is covered by the detection hypothesis and vice versa (see Figure 10). A detection is considered true if dr≤0.5 (corresponding to a deviation up to 25% of the true object size) and cover and overlap are both above 50%. Only one hypothesis per object is accepted as correct, so any additional hypothesis on the same object is considered as a false positive.

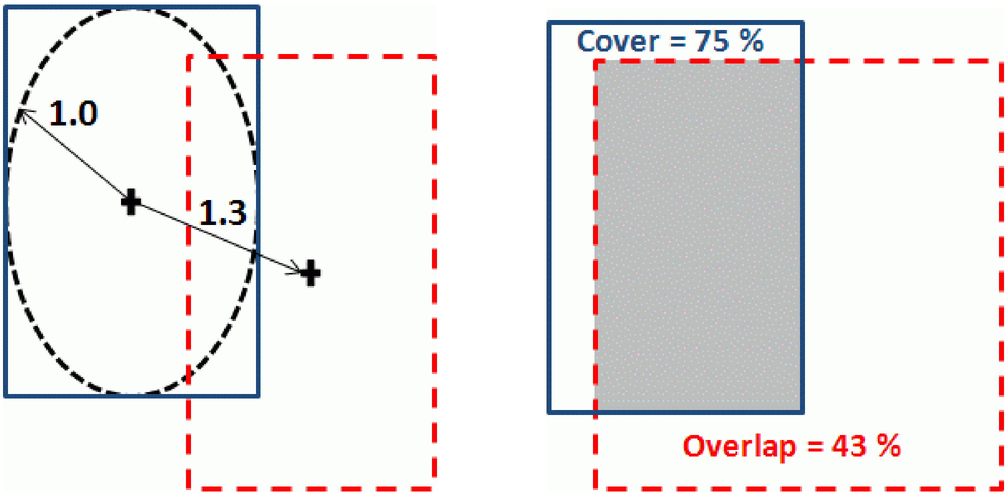


Figure 10 – Evaluation criteria for comparing bounding boxes [40] (left) relative distance; (right) cover and overlap

Often we use, the integrated Average Precision (AP) to summarize the overall performance, represented geometrically as the area under the PR curve (AUC-PR), in order to express more clearly the results we have chosen the representation Recall vs 1-Precision (see Figure 11). In addition, focusing on the people detection evaluation in video security systems, we want also to evaluate the detector at the operating point, i.e., at the predefined optimal decision threshold for each algorithm. Thus we can compare the final operational performance and not just its overall performance.

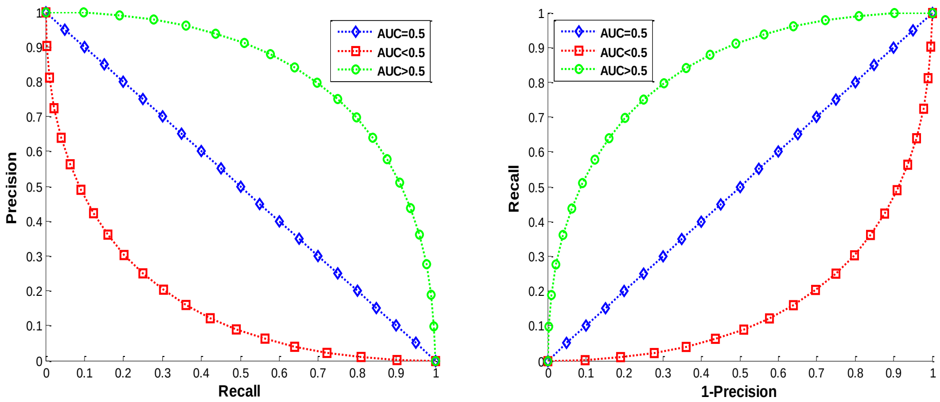


Figure 11 – Precision-Recall curves and area under the curve. Equivalent representations: Precision vs Recall representation and Recall vs 1-Precision representation.

4.1.3. Video object tracking

In order to evaluate the accuracy selected tracking algorithms, one metric was chosen: SFDA (Sequence Frame Detection Accuracy) which calculates for each frame the spatial overlap between the estimated target location and the ground-truth annotation.

$$\boldsymbol{SFDA} = \frac{\sum_{t=1}^{N_{frames}} FDA(t)}{\sum_{t=1}^{N_{frames}} \exists (N_{GT}^{t}\ OR\ N_{D}^{t})} \qquad (4.10)$$

$$FDA(t) = \frac{OverlapRatio}{\frac{N_{GT}^{t} + N_{D}^{t}}{2}} \qquad (4.11)$$

where N_{GT}^{t} and N_{GT}^{t} represent the number of ground-truth and target annotations respectively in the *th* frame.

4.1.4. Event detection

For matching event annotations and detections, we have defined the following criteria:

$$Match(E^{GT}, E^{D}) = \begin{cases} 1 \quad if & score & > & \rho & \wedge \\ & \left|T_{start}^{D} - T_{start}^{GT}\right| & < & \tau_1 & \wedge \\ & \left|T_{end}^{D} - T_{end}^{GT}\right| & < & \tau_2 & \wedge \\ & \dfrac{2\left|A^{GT} \cap A^{D}\right|}{\left|A^{GT}\right|^2 + \left|A^{D}\right|^2} & > & \sigma & \\ 0 & Otherwise & & & \end{cases} \quad (4.12)$$

where E^{GT} and E^{D} are the annotated and detected events; score is the probability of the detected event; (T_{start}^{D}; T_{end}^{D}) and (T_{start}^{GT}; T_{end}^{GT}) are the frame intervals of the annotated (GT) and detected (D) events; A^{GT} and A^{D} represent the average area (in pixels) of each event; $\left|A^{GT} \cap A^{D}\right|$ is their average spatial overlap (in pixels); ρ, τ_1, τ_2 and σ are positive thresholds (heuristically set to the values $\rho = 0.75$, $\tau_1 = \tau_2 = 100$, and $\sigma = 0.5$).

Then, we evaluate the recognition accuracy with the Precision (P) and Recall (R) measures. Precision is the ratio between the correct and the total number of detections. Recall is the ratio between the correct detections and the total number of annotations. They are defined as follows

$$\textbf{\textit{Recall}} = \frac{TP}{TP + FN} \quad (4.13)$$

$$\textbf{\textit{Precision}} = \frac{TP}{TP + FP} \quad (4.14)$$

where TP (True Positive) are the correct event detections, FN (False Negatives) are the missed events and FP (False Positive) are the wrong event detections. For event annotation and performance evaluation, the ViPER toolkit has been used [25].

4.2. Not based on ground-truth data

To extend the applicability of performance evaluation, empirical standalone methods for track-quality estimation without ground-truth data have been defined for large unlabeled datasets, self-tuning (automatic control via on-line analysis), algorithm comparative ranking and fusion. In this section, we review the approaches of the EventVideo project to be used in the video object segmentation and tracking stages.

4.2.1. Video object segmentation

We have selected the region-based measures based on color proposed by [26] and perform a slight modification for performance evaluation [27]. We have decided not to use measures from the other two described categories (model and assisted) because the constraints introduced (model of foreground regions and accuracy of the additional algorithm) are hard to satisfy. On the contrary, the matching of object and color region boundaries is usually satisfied for the video analysis domain. Consequently, the segmentation algorithms selected for the experiments do not include any foreground modeling.

The measure selected is the color contrast along the boundary [26]. It is based on defining normal lines of length 2L + 1 for each boundary pixel and comparing the color differences between the initial (PI) and ending (PO) points of each normal line. The neighborhood of these pixels is also considered by using a window of size MxM. The scheme is depicted in **Figure 12** It proposes to estimate the segmentation quality of each boundary pixel using the Boundary Spatial Color Contrast feature defined as follows:

$$BSCC(t;i) = \frac{\left\| C_O^i(t) - C_I^i(t) \right\|}{\sqrt{3 \cdot 255^2}}, \qquad (4.15)$$

where $C_O^i(t)$ and $C_I^i(t)$ are the mean colors calculated in the MxM neighborhood of the points PI and PO (using the RGB color space quantified into 256 levels) for each i-th boundary pixel of the foreground region at time t. This measure ranges from 0 to 1 depending if all pairs of mean colors belong to, respectively, the same or different color regions.

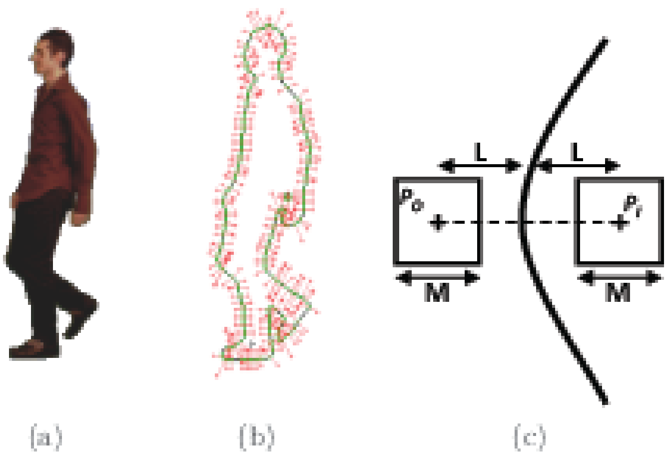


Figure 12 – Boundary-based contrast scheme proposed by [26]**. (a) Segmented object, (b) its boundary with the normal lines and (c) a zoom on a boundary pixel location**

Then, it proposes to evaluate the foreground segmentation of each object, Oj, and to combine the segmentation of multiple objects as follows:

$$DC1_{O_j}(t) = \frac{1}{K_t}\sum_{i=1}^{K_t} BSCC(t;\, i,\, j),$$

$$DC1(t) = \min_j \left(DC1_{O_j}(t)\right), \qquad (4.16)$$

where Kt is the total number of boundary pixels, BSCC is the spatial color contrast of the i-th boundary pixel of the j-th foreground region being analyzed. Its value ranges from 0 (lowest segmentation quality) to 1 (highest segmentation quality). Additionally, [26] used this measure to detect incorrectly segmented boundary pixels if they are above a certain threshold, T1. Thus, a second measure of segmentation quality could be derived by counting the correctly segmented boundary pixels as follows.

$$DC2_{O_j}(t) = \frac{\#(BSCC(t;\, i,\, j) > T_1)}{K_t},$$

$$DC2(t) = \min_j \left(DC2_{O_j}(t)\right). \qquad (4.17)$$

The main advantages of these measures are their low complexity and their possibility to detect failures at finer level (boundary pixel). These aspects make the measure useful for its use to adapt or feedback real-time video segmentation algorithms to improve the segmentation performed. The parameters (of this measure) to study are the normal line length L, the size M of the window around PI=PO points and the threshold, T1, used in the DC2 measure. As it can be observed the two measures based on color, DC1 and DC2, fall in the range [0; 1].

4.2.2. Video object tracking

For estimating tracking performance without ground-truth information, we use a state-of-the-art approach [28] based on estimating the uncertainty of the tracker and then, analyzing its values to decide whether the tracker is on the target or on background.

The uncertainty of the tracking filter (i.e., algorithm) can be used as indicator of unstable periods of the output data (e.g., wrong target estimation) providing information about the tracker condition. We measure the tracker uncertainty using the spatial uncertainty of the N particles (following the particle filter approach). This uncertainty can be estimated by analyzing the eigenvalues of the covariance matrix [4]. Hence, we compute such uncertainty as follows:

$$S_t = \sqrt[d]{det(\Sigma_t)}, \tag{4.18}$$

where Σ_t is the covariance matrix of the posterior distribution of the tracking filter [4], *det(.)* is the matrix determinant and *d* is the number of dimensions of the state space of the filter.

For identifying when the tracker is stable (i.e., following the target), we study the changes of St within a time window of length λ. We compute two relative variations of uncertainty for the change of $S_{t-\lambda}$ with respect to St and vice-versa as defined in [28]. The former indicates low-to-high uncertainty changes whereas the latter represents high-to-low uncertainty changes. Two time window lengths are used for considering short-term and long-term changes (λ_1 and λ_2). As a result, four signals are computed by combining the two relative variations and the two window lengths. Then, they are thresholded for detecting the uncertainty transitions with three thresholds (τ_1, τ_2 and τ_3) as proposed in [28]. Finally, these detections are combined by means of a finite-state machine to decide the tracker condition: focused on the target, scanning the video frame for the target or locking on the target after a tracking failure [28]. **Figure 14** shows an example of such estimation of tracker condition.

Then, we use time-reversed analysis to check the tracker recovery when it focuses on an object after unsuccessful operation as it might be on a distractor (background objects with features similar to those of the target). This analysis is based on applying a tracker in reverse direction from this recovery instant until a reference point (the last time instant when the tracker was successful) [28]. Effective tracker recovery after failure is determined by thresholding (with τ_4) the spatial overlap between the tracker to be evaluated and the reverse tracker at the reference point. Note that the time-reversed analysis is required as the uncertainty is only able to determine if the tracker is following an object that might be the target or a distractor.

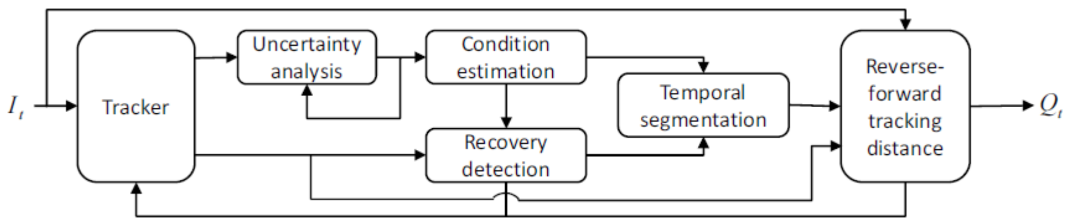


Figure 13 – Scheme of the performance evaluation approach without ground-truth data followed in the EventVideo project [28]

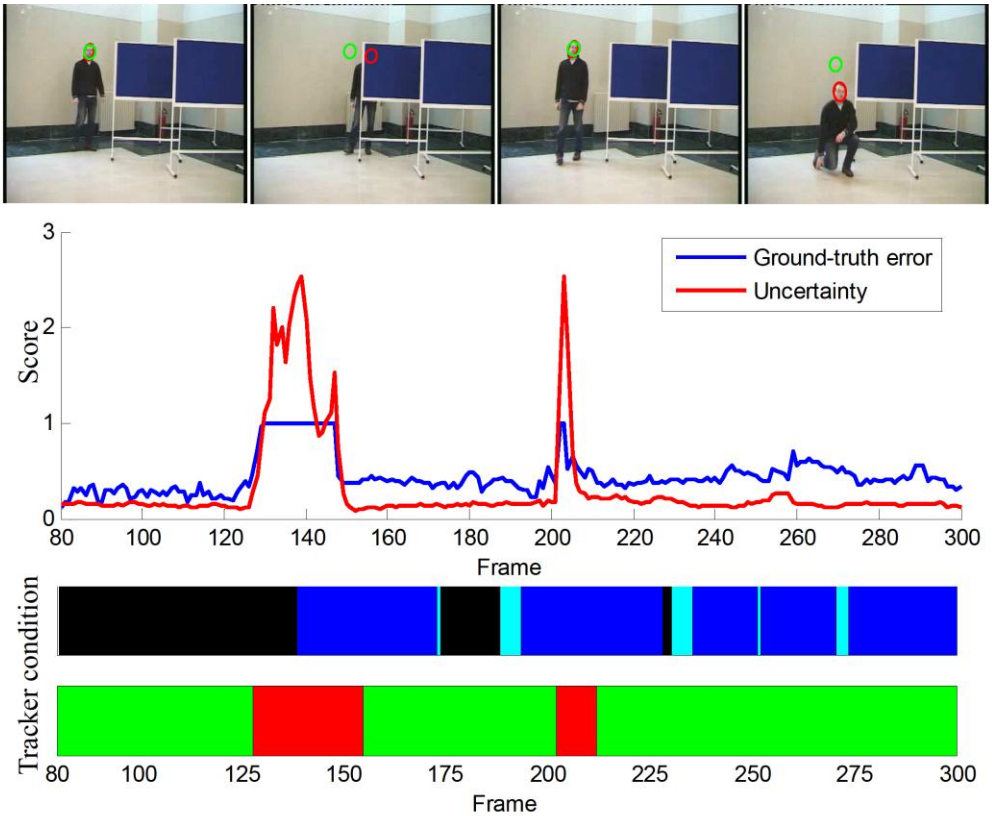


Figure 14 – Tracking results, tracker condition estimation and temporal segmentation for target H5 (occlusion_1 sequence; frames shown are 100, 140, 180 and 210). Tracking results and ground-truth annotations are represented as green and red ellipses, respectively. (Green: successful tracking; Red: unsuccessful tracking; Black: scanning; Cyan: locking in; Blue: locked on.)

5. Conclusions

In this document, we have presented the material to be used for performance evaluation within the EventVideo project. In particular, we have selected some stages for evaluation: video object segmentation, people modeling and detection, video object tracking and event detection. Then, we have described the datasets used in section 3 (CVSG, PDds, SOVTds, ASODds y EDds; all of them available at http://dymas.ii.uam.es/webvpu/en/recursos-publicos/datasets/) and the methodologies for the evaluation of each stage in section 4. Moreover, a novel methodology that does not follow the traditional approach based on ground-truth information has been presented in section 4.2 for the video object segmentation and tracking stages.

Moreover, according to the scenario classification proposed in section 2.2 (with the variables complexity and density), the datasets to be used in the EventVideo project can be categorized as illustrated in the following figure.

<table>
<tr><td colspan="2" rowspan="2"></td><th colspan="2">Density</th></tr>
<tr><th>Low</th><th>High</th></tr>
<tr><th rowspan="2">Complexity</th><th>Low</th><td>CVSG
PDds
SOVTds
ASODds
EDds</td><td>PDds (-)
ASODds (-)</td></tr>
<tr><th>High</th><td>CVSG
PDds (-)
SOVTds (-)
EDds (-)</td><td></td></tr>
</table>

Figure 15 – Classification of datasets according to criteria defined in section 2.2. The (-) indicates that the dataset partially fulfills the requirements of such criterion.

As future work for this task of the EventVideo project, the selected datasets will be used for comparing the most recent algorithms in order to evaluate the current status of the state-of-the-art (and which of the criteria in **Figure 15** could be considered as achieved). Moreover, we will consider the extension of the datasets to cover the highest levels of the defined situations and the inclusion of additional information to help visual analysis (such as depth and laser)

6. References

[1] H. Dee and S.Velastin, “How close are we to solving the problem of automated visual surveillance?”, Machine Vision and Applications, 19(5):329-343, May 2008

[2] B. Greoris, F. Bremond, M. Thonnat, “Real-time control of video surveillance systems with program supervision techniques”, Machine Vision and Applications, 18(3):185-205, March 2007

[3] A. Baumann, M. Boltz, J. Ebling, M. Koenig, H. S. Loos, M. Merkel, W. Niem, J. K.Warzelham, and J. Yu. “A review and comparison of measures for automatic video surveillance systems”. EURASIP Journal on Image and Video Processing, 2008:1-30, 2008.

[4] E. Maggio and A. Cavallaro. Video tracking: theory and practice. Wiley, 2011.

[5] H.Wu, A. Sankaranarayanan, and R. Chellappa. “Online empirical evaluation of tracking algorithms”. IEEE Trans. Pattern Anal. Mach. Intell., 32(8):1443–1458, Aug. 2010.

[6] J. C. SanMiguel, A. Cavallaro, J. M. Martinez “Evaluation of on-line quality estimators for object tracking”, en Proc. of 2010 IEEE Int. Conf. on Image Processing, Hong Kong (China), Septiembre 2010 , pp . 825-828

[7] L Caro Campos, J. C. SanMiguel y J. M. Martínez. “Discrimination of abandoned and stolen object based on active contours “,en Proc. of 2011 IEEE Int. Conf. on Advanced Video and Signal based Surveillance, Klagenfurt (Austria), Septiembre 2011 pp. 101-106,

[8] J.C. SanMiguel and J.M. Martínez, "Robust unattended and stolen object detection by fusing simple algorithms", Proc. of IEEE Int. Conf. on Advanced Video and Signal based Surveillance, AVSS2011, SantaFe (NM, USA), pp. 18-25.

[9] J. C. SanMiguel, M. Escudero-Viñolo, J. M. Martínez y J. Bescós, “Real-time single-view video event recognition in controlled environments”, en Proc. of the 9th Int. Workshop on Content-Based Multimedia Indexing, CBMI’2011, Madrid, España, Junio 2011, pp. 91-96.

[10] F. Tiburzi, M. Escudero, J. Bescós, J. M. Martinez: "A ground-truth for Motion-based Video-object Segmentation", Proc. of 2008 IEEE International Conference on Image Processing (ICIP), San Diego, (CA, U.S.A), pp. 17-20, 2008.

[11] http://imagelab.ing.unimore.it/vssn06/

[12] http://media.ee.ntu.edu.tw/Archer_contest/

[13] http://www.changedetection.net/

[14] Brutzer, Sebastian; Höferlin, Benjamin; Heidemann, Gunther: “Evaluation of Background Subtraction Techniques for Video Surveillance”, Proc. of Computer Vision and Pattern Recognition (CVPR), Colorado Springs (CO, USA), pp. 1937-1944, 2011.

[15] Alvaro García, Jose M. Martinez, Jesús Bescós: "A corpus for benchmarking of people detection algorithms", Pattern Recognition Letters, 33 (2): pp. 152-156, January 2012, ISSN 0167-8655

[16] “Mit traffic data set,” http://www.ee.cuhk.edu.hk/ xgwang/ MITtraffic.html, Last accessed, 24 May 2012.

[17] “Institut fur Algorithmen und Kognitive Systeme: Cars Dataset,” http://i21www.ira.uka.de/image-sequences/, Last accessed, 24 May 2012

[18] “TRECVID 2009 Event Detection Dataset,” http://trecvid.nist.gov/trecvid.data.html, Last accessed, 24 May 2012.

[19] S. Birchfield, “Elliptical Head Tracking Using Intensity Gradients and Color Histograms,” http://www.ces.clemson.edu/ stb/research/headtracker/.

[20] R. Vezzani and R. Cucchiara, “Video surveillance online repository (visor): an integrated framework,” Multimedia Tools App., vol. 50, no. 2, pp. 359–380, nov 2010

[21] “SPEVI, surveillance performance evaluation initiative,” http://www.eecs.qmul.ac.uk/andrea/spevi.html, Last accessed, 24 May 2012.

[22] PETS, “PETS, IEEE int. workshop perform. eval. track. surveill.,” Last accessed, 24 May 2012.

[23] “CAVIAR context aware vision using image-based active recognition,” http://homepages.inf.ed.ac.uk/rbf/CAVIAR/, Last accessed, 24 May 2012.

[24] “I-LIDS dataset for avss 2007,” http://www.avss2007.org/, Last accessed, 24 May 2012.

[25] D. Doermann and D. Mihalcik. Tools and techniques for video performances evaluation. In Proc. Of IEEE Int. Conf. on Pattern Recognition, pages 161-170, Cambrigde (UK), 23-26 Aug. 2000.

[26] C. Erdem, E. Sankur, and A. Tekalp. Performance measures for video object segmentation and tracking. IEEE Trans. on Image Processing, 13(7):937-951, July 2004a

[27] Juan C. SanMiguel y José M. Martínez. “On the evaluation of background subtraction algorithms without ground-truth“,en Proc. of 2010 IEEE Int. Conf. on Advanced Video and Signal based Surveillance, Boston (USA), September 2010 pp. 180-187

[28] Juan C. SanMiguel, Andrea Cavallaro y José M. Martínez, “Adaptive online performance evaluation of video trackers”, IEEE Transactions on Image Processing, 21(5): 2812-2823, Mayo 2012

[29] Andriluka, M.; Roth, S.; Schiele, B.: "People-tracking-by-detection and people-detection-by-tracking", Proc. of Computer Vision and Pattern Recognition (CVPR), Anchorage, (Alaska, USA), pp. 1-8, 2008.

[30] Enzweiler, M.; Gavrila, D.M.: "Monocular Pedestrian Detection: Survey and Experiments" IEEE Transactions on Pattern Analysis and Machine Intelligence, vol.31, no.12, pp.2179-2195, Dec. 2009.

[31] Dollar, P.; Wojek, C.; Schiele, B.; Perona, P.: "Pedestrian detection: A benchmark", Proc. of Computer Vision and Pattern Recognition (CVPR), Miami Beach (FL, USA), pp.304-311, 2009.

[32] Ess, A.; Leibe, B.; Van Gool, L.; "Depth and Appearance for Mobile Scene Analysis", Proc. of International Conference Computer Vision (ICCV), Rio de Janeiro (Brasil), pp.1-8, 2007.

[33] N. Dalal and B. Triggs. Histograms of oriented gradients for human detection. In Proc. of CVPR, pages 886-893, 2005.

[34] P. Dollár, C. Wojek, B. Schiele, and P. Perona. Pedestrian detection: An evaluation of the state of the art. IEEE Transactions on Pattern Analysis and Machine Intelligence, 34(4):743-761, 2012.

[35] S. Munder and D. M. Gavrila. An experimental study on pedestrian classification. IEEE Trans. on Pattern Analysis and Machine Intelligence, 28(11):1863-1868, 2006.

[36] M. Enzweiler and D. M. Gavrila. Monocular pedestrian detection: Survey and experiments. IEEE Trans. on Pattern Analysis and Machine Intelligence, 31(12):2179-2195, 2009.

[37] M. Andriluka, S. Roth, and B. Schiele. People-tracking-by-detection and people-detection-by-tracking. In Proc. of CVPR, pages 1 8, 2008.

[38] B. Leibe, A. Leonardis, and B. Schiele. Robust object detection with interleaved categorization and segmentation. Int. Journal of Computer Vision, 77:259-289, 2008.

[39] C. Wojek, S. Walk, and B. Schiele. Multi-cue onboard pedestrian detection. In Proc. of CVPR, pages 794-801, 2009.

[40] B. Leibe, E. Seemann, and B. Schiele. Pedestrian detection in crowded scenes. In Proc. of CVPR, pages 878-885, 2005.

Appendix

7. Additional datasets for evaluation

In this appendix, we list additional datasets for the evaluation of the selected stages in the EventVideo project.

7.1. Video object segmentation

7.1.1. VSSN2006

The VSSN Workshop 2006 [11] included a motion segmentation for surveillance competition. The artificial data input sequences and corresponding ground-truth data were provided in order to have a common framework for a fair comparison of the algorithms.

- Description: Each test video will consist of a video consisting of some (maybe dynamic) background and one or several foreground objects and a foreground mask video (ground truth video) specifying each pixel belonging to a foreground object (pixel values above 128; same pixel values belong to the same object, while different values belong to different objects).

- Number of sequences: 10 sequences with ground truth and 4 sequences without ground truth.

- Format: Color video of size 320x240 or 384x240 at 25 fps.

- Segmentation ground-truth available: yes.

- Estimated complexity: S1-S2.

7.1.2. IPPR06

The IPPR contest motion segmentation dataset [12] includes 3 different context of walking persons.

- Description: Simple dataset that includes 3 different context of walking persons and the segmentation of person is provided.

- Number of sequences: 3 sequences.

- Format: Color video of size 320x240 at 5 or 15 fps.

- Segmentation ground-truth available: yes.

- Estimated complexity: S1.

Figure 16 – Sample frames for the IPPR06 dataset

7.1.3. Change Detection 2012

The IEEE Workshop on Change Detection 2012 [13] aims to initiate a rigorous and comprehensive academic benchmarking effort for testing and ranking existing and new algorithms for change and motion detection much.

- Description: It is representative of indoor and outdoor visual data captured today in surveillance and smart environment scenarios. This dataset contains 6 video categories with 4 to 6 videos sequences in each category.
- Number of sequences: 31 sequences.
- Format: Color video or thermal JPEG frames of multiple sizes.
- Segmentation ground-truth available: yes.
- Estimated complexity: S1-S2.

Figure 17 – Sample frames for the Change Detection dataset

7.1.4. SABS

The SABS (Stuttgart Artificial Background Subtraction) dataset [14] is an artificial dataset for pixel-wise evaluation of background models. The use of artificial data enables to separably judge the performance of background subtraction methods for each of the challenges background subtraction has to cope with.

- Description: The dataset consists of video sequences for nine different challenges of background subtraction for video surveillance. These sequences are further split into training and test data. For every frame of each test sequence ground-truth annotation is provided as color-coded foreground masks.
- Number of sequences: 9 sequences.
- Format: Color video of size 800x600 at 30 fps.
- Segmentation ground-truth available: yes.
- Estimated complexity: S1-S2.

Figure 18 – Sample frames for the SABS dataset: Ground-truth annotation, frame of artificial video footage and Shadow annotation

7.2. People modelling and detection

7.2.1. TUD-Pedestrians

The TUD Pedestrians dataset [29] from Micha Andriluka, Stefan Roth and Bernt Schiele consists of training images and test sequences.

- Description: The TUD pedestrian dataset consists of 250 images with 311 fully visible people with significant variation in clothing and articulation and 2 video sequences with highly overlapping pedestrians with significant variation in clothing and articulation.

- Number of sequences: 2 sequences, 272 frames.
- Format: Color video frames of size 640x480.
- People detection ground-truth available: yes.
- Estimated complexity scenario: S3.

Figure 19 – Sample frames for the TUD-Pedestrians dataset

7.2.2. DCII

- Description: The Daimler Mono Pedestrian Detection Benchmark Data Set II [30] consist of a large sequence captured from a moving vehicle in a 27-minute drive through urban traffic.
- Number of sequences: 1 sequences, 21791 frames.
- Format: Color video frames of size 640x480.
- People detection ground-truth available: yes.
- Estimated complexity scenario: S3.

Figure 20 – Sample frames for the DCII dataset

7.2.3. Caltech Pedestrian Dataset

The Caltech Pedestrian Dataset [31] consists of approximately 10 hours of 640x480 30Hz video taken from a vehicle driving through regular traffic in an urban environment. About 250,000 frames (in 137 approximately minute long segments) with a total of 350,000 bounding boxes and 2300 unique pedestrians were annotated. The annotation includes temporal correspondence between bounding boxes and detailed occlusion labels.

- Description: Approximately 10 hours of 640x480 30Hz video taken from a vehicle driving through regular traffic in an urban environment.
- Number of sequences: 1 sequences, 250000 frames.
- Format: Color video frames of size 640x480.
- People detection ground-truth available: yes.
- Estimated complexity scenario: S3.

Figure 21 – Sample frames for the Caltech Pedestrian dataset

7.2.4. ETHZ

- Description: Data [32] was recorded using a pair of AVT Marlins mounted on a chariot, with a resolution of 640 x 480 (bayered), and a framerate of 13-14 FPS. For each dataset, it provides the unbayered images for both cameras, the camera calibration, as well as the set of annotations. Depth maps were created based on this data using the publicy available belief-propagation-based stereo algorithm of Huttenlocher and Felzenszwalb.

- Number of sequences: 4 sequences, 2293 frames.

- Format: Stereo-color video frames of size 640x480.

- Tracking ground-truth available: yes.

- Estimated complexity scenario: S3.

Figure 22 – Sample frames for the ETHZ dataset

7.3. Video object tracking

7.3.1. SPEVI

The Surveillance Performance EValuation Initiative (SPEVI) [21] is a set of links of publicly available datasets for researches. The videos can be used for testing and evaluating video tracking algorithms for surveillance-related applications. Two datasets are especially interesting regarding the tracking evaluation and they are described as follows.

Single Face Dataset

- Description: this is a dataset for single person/face visual detection and tracking. The sequences include different illumination conditions and resolutions.

- Number of sequences: 5 sequences, 3018 frames.

- Format: individual JPEG images.
- Tracking ground-truth available: yes
- Estimated complexity scenario: S1

Multiple Face Dataset

- Description: this is a dataset [21] for multiple people/faces visual detection and tracking. The sequences (same scenario) contain 4 targets which repeatedly occlude each other while appearing and disappearing from the field of view of the camera.
- Number of sequences: 3 sequences, 2769 frames.
- Format: individual JPEG images.
- Tracking ground-truth available: yes.
- Estimated complexity scenario: S1

Figure 23 – Sample frames for the SPEVI dataset (top: single object, down: multiple object)

7.3.2. ETISEO

ETISEO [35] is a video understanding evaluation project that contains the following data:

- Description: it contains indoor and outdoor scenes, corridors, streets, building entries, subway.... They also mix different types of sensors and complexity levels.
- Number of sequences: 86 sequences.
- Tracking ground-truth available: yes.
- Estimated complexity scenario: S1-S3

Figure 24 – Sample frames for the ETISEO dataset

7.3.3. PETS

PETS [22] is the most extended database nowadays. A new database is released each year since 2000, along with a different challenge proposed. With the algorithms provided researchers can test or develop new algorithms. The best ones are presented in the conference held each year.

Since the amount of data is extensive and cover real situations, these databases are by far the most used and are almost considered a de facto standard. Despite this, it is important to say that the PETS databases are not ideal. One of its disadvantages is the fact that since PETS became a surveillance project, the challenges proposed are focused on high level applications of that field, leaving aside the tracking approach. Therefore, some important issues (such as illumination or target scale changes) are not considered.

PETS2000

- Description: Outdoor people and vehicle tracking (single camera).
- Number of sequences: 1 set of training and test sequence.
- Training sequence: 3672 frames.
- Test sequence: 1452 frames.
- Formats: MJPEG movies and JPEG frames.

- Tracking ground-truth available: no.
- Estimated complexity scenario: S1

PETS 2001

- Description: Outdoor people and vehicle tracking (two synchronized views; includes omnidirectional and moving camera). Challenging in terms of significant lighting variation, occlusion, scene activity and use of multi-view data.
- Number of sequences: 5 sets of training and test sequences
- Training sequences: 1st) 3064 frames. 2nd) 2989 frames. 3rd) 5563 frames. 4th) 6789 frames. 5th) 2866 frames.
- Test sequences: 1st) 2688 frames. 2nd) 2823 frames . 3rd) 5336 frames. 4th) 5010 frames. 5th) 2867 frames.
- Formats (for each set): MJPEG movies and JPEG frames.
- Tracking ground-truth available: no.
- Estimated complexity: S1

PETS 2006

- Description: Multicamera person and baggage detection in a train station. Scenarios of increasing complexity, captured using multiple sensors.
- Number of sequences: 7 sets with 4 cameras each.
- Formats (for each set): MJPEG movies and JPEG frames.
- Tracking ground-truth available: no.
- Estimated complexity: S1-S3

Figure 25 – Sample frames for the PETS2006 dataset

PETS 2007

- Description: multicamera setup containing the following scenarios: loitering; attended luggage removal (theft) and unattended luggage with increasing scene complexity.
- Number of sequences: 1 training set + 9 testing sets.
- Formats (for each set): JPEG frames.
- Tracking ground-truth available: no.
- Estimated complexity: S1-S3

Figure 26 – Sample frames for the PETS2007 dataset

PETS 2010

- Description: multicamera setup containing di_erent crowd activities (these datasets are the same as used for PETS2009).

- Number of sequences: 1 training set + 3 testing sets.
- Estimated complexity: S1-S3

Figure 27 – Sample frames for the PETS2010 dataset

7.3.4. CAVIAR

The main objective of CAVIAR [23] is to address the scientific question: Can rich local image descriptions from foveal and other image sensors, selected by a hierarchical visual attention process and guided and processed using task, scene, function and object contextual knowledge improve image-based recognition processes [REF]. Several methods were researched in order to address this question, including different areas, and the results were integrated in a closed-loop object and situation recognition system.

- Description: this dataset includes sequences of people walking alone, meeting with others, window shopping, entering and exiting shops, fighting and passing out and leaving a package in a public place. All video clips were filmed with a wide angle camera lens, and some scenarios were recorded with two different points of view (synchronized frame by frame).
- Number of sequences: INRIA (1st set): 6 sequences, Shopping Center in Portugal (2^{nd} set): 11 sequences, 6 different scenarios.
- Formats (for both sets): MJPEG movies, JPEG frames, XML ground-truth.
- Tracking ground-truth available: yes.
- Estimated complexity: S1

Figure 28 – Sample frames for the CAVIAR dataset

7.3.5. VISOR

The VIdeo Surveillance Online Repository is an extensive database containing a large set of multimedia data and the corresponding annotations. The repository has been conceived as a support tool for different research projects [20]. Some videos are available publicly; however, most of them are restricted and can only be viewed after a registration. The videos in the database cover a wide range of scenarios and situations, including (but not limited to) videos for human action recognition, outdoor videos for face detection, indoor videos for people tracking with occlusions, videos for human recognition, videos for vehicles detection and traffic surveillance.

- Description: this dataset includes several videos with a wide range of occlusions caused by objects or people in the scene. All of them include base annotations and some also include automatic annotations.
- Number of sequences: 6 sequences.
- Format: MJPEG movies.
- Tracking ground-truth available: no.
- Estimated complexity: S1

Figure 29 – Sample frames for the VISOR dataset

7.3.6. iLids

The Imagery Library for Intelligent Detection Systems (i-Lids) bag and vehicle detection challenge was included in the 2007 AVSS Conference [21].

- Description: this dataset includes several sequences for two separate tasks: _rst, an abandoned baggage scenario and second, a parked vehicle scenario.
- Number of sequences: 7 sequences (3 for Task 1, 4 for Task 2)..
- Format: JPEG images, 8-bit color MOV, XML for ground-truth.
- Tracking ground-truth available: no.
- Estimated complexity: S1-S2-S3

Figure 30 – Sample frames for the i-LIDS dataset

7.3.7. Clemson dataset

Included in an elliptical head tracking project by Stan Birchfield there is a series of videos very interesting for head tracking. The sequences include issues such as occlusion, rotation, translation, clutter in the scene, change in the target's size, etc. The tracker as well as the sequences can be found at the web [19].

- Description: this dataset includes several sequences for head tracking with di_erent targets.
- The videos include some of the most important issues for tracking algorithms.
- Number of sequences: 16 short sequences (1350 frames in total).
- Format: BMP images.
- Ground-truth available: yes.
- Estimated complexity: S1-S2

Figure 31 – Sample frames for the CLEMSON dataset

7.3.8. MIT Traffic Dataset

MIT traffic dataset is for research on activity analysis and crowded scenes. It includes a traffic video sequence of 90 minutes long recorded by a stationary camera. The size of the scene is 720 by 480. More information regarding this work can be found in [16].

- Description: this dataset includes several clips regarding traffic. It contains a representation of most of the issues previously described, making this a very interesting dataset.

- Number of sequences: 1 sequence, 165880 frames divided in 20 clips.
- Estimated complexity: S1-S2

Figure 32 – Sample frames for the MIT traffic dataset

7.4. Event detection

In this section, we list the existing datasets for abandoned and stolen object detection task. They are:

7.4.1. PETS 2006

- URL: http://www.cvg.rdg.ac.uk/PETS2006/data.html
- This dataset consists on different examples of left-luggage events, with increasing scene complexity in terms of nearby people. A total of 6 left-luggage events in a railway station are recorded by four cameras positioned at different angles (28 videos in total). Videos from this data set are between 1 and 2 minutes long, with standard PAL resolution (768x576 pixels, 25fps).

7.4.2. PETS 2007

- URL: http://www.cvg.rdg.ac.uk/PETS2007/data.html
- This dataset contains 8 examples of abandoned luggage at an airport. Each event is recorded by four different cameras. Additionally, a background training sequence is provided. Complexity is defined with the following criteria: loitering, stolen luggage and abandoned luggage. Video sequences have been recorded in a dense, crowded scenario. Videos are between 2 and 3 minutes long, with standard PAL resolution (768x576 pixels, 25fps).

7.4.3. AVSS 2007

- URL: http://www.eecs.qmul.ac.uk/~andrea/avss2007_d.html

- This dataset has 3 sequences containing abandoned object events at an underground station, with 3 complexity levels: easy, medium, and hard, defined in terms of the density of the crowd. Each sequence is about 3.5 minutes long, with PAL resolution.

7.4.4. CVSG

- URL: http://www-vpu.eps.uam.es/CVSG/

- In this dataset, different sequences have been recorded using chroma based techniques for simple extraction of foreground masks. Then, these masks are composed with different backgrounds. Provided sequences have varying degrees of difficulty in terms of foreground segmentation complexity. Sequences contain examples of abandoned objects and objects removed from the scene.

7.4.5. ViSOR

- URL: http://www.openvisor.org/

- This dataset is classified in different categories including outdoor and indoor events (human actions, traffic monitoring, cast shadows. . .). A total of 9 abandoned-object sequences are included, recorded in an indoor setting. These are low-complexity sequences. Videos are around 10 seconds long and are provided at 320x256@25fps resolution.

7.4.6. CANDELA

- URL: http://www.multitel.be/~va/candela/abandon.html

- This dataset contains 16 examples of abandoned objects inside a building lobby, with different interactions between object owners. Videos are around 30 seconds long, provided at 352x288 resolution. Despite the simplicity of the scenario, the low resolution and the relatively small size of objects present challenges for foreground segmentation.

7.4.7. CANTATA

- URL: http://www.multitel.be/~va/cantata/LeftObject/

- Videos from these dataset contain examples of left objects. A total of 31 sequences of 2 minutes have been recorded with two different cameras. Some videos include a number of people leaving objects in the scene (abandoned objects) and other videos show people removing the same objects from the scene (stolen objects). Videos are provided at standard PAL resolution, compressed using MPEG-4.

Figure 33 – Sample frames for available datasets of abandoned object detection