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**ONLINE CONTEXTUAL UPDATING
IN MULTI-CAMERA SCENARIOS**

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-MASTER THESIS-

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Abstract

The following project has been proposed to achieve two main objectives. The first one aims to develop a system capable of perform pedestrian detection and semantic segmentation over a multi camera system. The fusion of both disciplines leads to combine pedestrian and semantic information in order to constrain detections. Also, the multi camera system is used to reproject detections from one camera to the others to improve accuracy. In addition, statistical data usage of concrete semantic areas is also extracted. Second objective is related to the development of a Graphical User Interface (GUI) from which algorithms can be controlled and results can be displayed.

In order to achieve these objectives a state of the art study has been done. Pedestrian detection approaches are deeply reviewed including those that need object proposals. Also, recent trends nowadays and next steps in the scope of Pedestrian Detection are analyzed. In addition, actual state of the art regarding contextual information and in concrete, semantic segmentation is studied. Finally, multi camera scenarios configurations are described.

A multithread application has been developed and analyzed to, as mentioned before, present results and tune different algorithms.

A new system has been proposed in order to achieve the objectives and perform pedestrian detections under different filtering and fusion conditions. Detectors such as HOG, DPM or PSP-Net have been integrated and a complete semantic segmentation has been performed. Both information has been combined in a common developed frame.

Finally, system performance has been tested in a generated dataset with manually annotated ground truth.

Keywords

Pedestrian detection, multi camera, semantic segmentation, cenital plane.

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Contents

Abstract	v
Acknowledgements	vii
1 Introduction	1
1.1 Motivation	1
1.2 Objectives	2
1.3 Thesis Structure	3
2 State of the Art	5
2.1 Pedestrian Detection	5
2.1.1 Pedestrian Detection Approaches	6
2.1.2 Object Proposals	10
2.1.3 Next Steps Towards Generic PD	10
2.2 Contextual Information	11
2.2.1 Global	11
2.2.2 Local	12
2.2.3 Offline	12
2.2.4 Online	12
2.2.5 Semantic Segmentation	12
2.3 Multi-camera scenarios	15
3 Developed Application	19
3.1 Single-thread Engineer Application	20
3.2 Multi-thread Engineer Application	22
3.2.1 Classes Distribution	27
3.3 Multi-thread User Application	28
4 Proposed System	31
4.1 Contextual Model Generation	31
4.2 Pedestrian Detection	34
4.2.1 Histogram of Oriented Gradients	35
4.2.2 Deformable Part Model	35
4.2.3 Aggregated Channel Features Detector	36
4.2.4 Fast Region-Based Convolutional Network	37

4.2.5	PSP-Net	38
4.3	Fusion and Filtering	38
4.3.1	Multi-camera Scenario	38
4.3.2	Pedestrian Filtering and Constraining	47
4.4	Reference and Inertial Homography Planes	52
4.4.1	Semantic and RGB Reference Plane Generation	52
4.4.2	Semantic Fusion in the Reference Plane	53
4.4.3	Parametric Homographies Between Inertial Planes	55
4.5	Statistical Usage Data	58
5	Results	61
5.1	Used Hardware	61
5.1.1	Camera Specifications	61
5.1.2	Camera User Web Interface (GUI)	63
5.2	Experiment Setup	64
5.2.1	Data-set	64
5.2.2	Ground Truth Generation	65
5.2.3	Evaluation Framework	67
5.3	Application Performance	68
5.3.1	Application Performance Results Discussion	69
5.4	Homography Calculation	69
5.4.1	Homography Results Discussion	70
5.5	Semantic Segmentation	70
5.5.1	Semantic Segmentation Results Discussion	70
5.6	Pedestrian Detection	70
5.6.1	Mono-Camera	73
5.6.2	Multi-Camera	73
5.6.3	Mono-Camera with Semantic Constraining	73
5.6.4	Multi-Camera with Semantic Constraining	73
5.6.5	Pedestrian Detection Results Discussion	73
5.7	Statistical Usage Data	73
5.7.1	Statistical Usage Data Results Discussion	74
5.8	Overall Discussion	79
6	Conclusions and Future Work	81
6.1	Conclusions	81
6.2	Future Work	81
Bibliography		83

List of Figures

2.1	Image summary from data-sets	6
2.2	Generic Pedestrian Detector Example Diagram.	8
2.3	Scene parsing on ADE20K data-set.	13
2.4	Semantic Segmentation result examples on Cityscapes Data-set.	16
3.1	QT Main Window Designer	20
3.2	Flow-chart legend	21
3.3	Flow-chart diagram for the single-thread application.	21
3.4	Flow-chart diagram for the multi-thread application.	23
3.5	Main application window.	24
3.6	Application menu bar	25
3.7	Options Menu.	26
3.8	Information Display	26
3.9	Results Display Area	27
3.10	Hierarchical representation of the code.	28
3.11	User version application main window.	29
4.1	Proposed system flowchart	32
4.2	Overview of the proposed PSPNet	33
4.3	HOG Pedestrian Descriptor	35
4.4	Example detection obtained with the DPM person model.	36
4.5	Aggregated Channel Features architecture.	37
4.6	Fast R-RCNN architecture.	38
4.7	Multi-camera configuration	39
4.8	Initial Camera Views	40
4.9	Generic homography problem. Camera and plane setup	41
4.10	First cenital plane approach	42
4.11	Second cenital plane approach with real measures	43
4.12	Second cenital plane approach with camera positions	43
4.13	Multi-camera configuration with panning set up	44
4.14	View selection process and homography calculation.	46
4.15	Cylinder estimation for camera instance projections	47
4.16	Cylinder estimation for cenital view projections.	48
4.17	Gaussian representation examples.	49
4.18	Pedestrian detection reprojection.	50

4.19	Pedestrian semantic constraining examples	51
4.20	RGB and semantic frames projected.	52
4.21	RGB Reference Planes	53
4.22	Semantic Median Average	54
4.23	Common semantic areas between pair of cameras.	56
4.24	Common semantic areas for all the cameras	57
4.25	Extending homography for parallel planes.	57
4.26	Set of inertial planes	58
4.27	Statistical semantic map.	59
5.1	Sony SNC-RZ50P Pan/Tilt Range diagram	62
5.2	Visualization and control menu	63
5.3	Preset position setting menu	63
5.4	Tour setting menu	64
5.5	Data-set example frames	65
5.6	Via Annotation Tool software main window	66
5.7	Annotated ground truth frames	66
5.8	Intersection over Union or Jaccard Index	68
5.9	Projected views with homography matrices	69
5.10	RGB frames and PSP-Net Semantic segmentation results	71
5.11	Recall / Precision graphs mono camera	73
5.12	Recall / Precision graphs multi camera	74
5.13	Recall / Precision graphs mono camera with semantic	75
5.14	Recall / Precision graphs multi camera with semantic	76
5.15	Statistical data usage curves in terms of pedestrian number/frames	76
5.16	Pedestrians paths usage along the Hall. Region of 40 pixels.	77
5.17	Pedestrians paths usage along the Hall. Region of 70 pixels.	78

List of Tables

2.1	Pedestrian Detection Performance.	9
2.2	Cityscapes Data-set Class Definitions	14
2.3	Cityscapes Data-set Challenge Results (Intersection over Union metric)	14
4.1	Final classes list from ADE20K to use in PSP-Net	34
5.1	Sony SNC-RZ50P Specifications	62
5.2	Comparison between the use of single thread or multi threads	68
5.3	Comparison between the use of single thread or multi threads	68
5.4	F-Score comparison for pedestrian detector approaches.	72

Chapter 1

Introduction

1.1 Motivation

Nowadays, we live surrounded by electronic devices which objective is to ensure the safety and security of the global population and to ease our lives on everyday tasks. These range from biometric systems [1] to all kind of different electrical sensors, including video surveillance cameras. These cameras are the ones that are of real interest when developing Image Processing and Computer Vision algorithms in the video surveillance scope [2].

The combination of these veins of research could lead to the automation of high-level human semantic tasks such as people detection [3], object detection and recognition [4, 5, 6] and extraction of contextual information [7]. The automation of these processes permits end-users build on these information sources to define the latest stages of video surveillance systems. These are usually the critical ones, e.g. alarm raising when some predefined event occurs.

Usually, mentioned video surveillance systems could be focus either on the analysis of a single-camera point of view, which will lead to a simple scenario in which the potential actions/events to detect will be observed from a single point in the scene or, on the analysis of a multi-camera setup. This last configuration will arise multiple benefits when analyzing big spaces as it will provide the user different views of the scene disambiguating occluded areas in the mono-camera views.

Among Computer Vision applications running on a multi-camera scenario, a pivotal field of research is the analysis of public spaces. These are often crowd-populated scenarios which analysis requires the combination of the data obtained by all recording cameras. It is of real interest to analyze people behavior patterns [8, 9, 10] and temporal usage of a given area in large-scale scenarios such as shopping malls, universities

and, generally, public-use buildings. Analysis range from the extraction of statistical measures of behavior to the detection of anomalous unexpected events [11]. This results may come from a combination of complementary algorithms such as contextual and semantic area classification, people detection and crowd behavior analysis.

1.2 Objectives

The main objective of this thesis is to extract contextual descriptions from a large-scale populated scenario while extracting temporal statistical usage data from relevant scene spaces using multiple cameras. This should be supported with a Graphical User Interface application.

To fulfill this objective, this work will embrace two different blocks of objectives that will complement each other. The first one will have to do with the design of a graphical user interface (GUI) whereas the second block will deal with algorithm and research-related objectives.

Graphical User Interface

The main user interface should be able to visualize and dynamically arrange -under a user-friendly environment-statistics from different areas of interest in a public space either pre-generated or generated under a real-time constraint.

Algorithm

The algorithm related objectives are:

1. To integrate a semantic segmentation algorithm to perform contextual element analysis in video sequences. The objective is to detect, classify and determine the spatial extend on each frame of the video of relevant elements such as doors, chairs, corridors and floor areas. We aim to:
 - (a) Identify the current state of all these elements in each of the processed cameras. The state should distinguish between visible and occluded.
 - (b) Identify the usage rate of some important elements of the scene measured by number of people per time interval.
2. To integrate state-of-the-art people detection algorithms results per view. To this aim, we need to:

- (a) Create a fusion mechanism to take advantage of the multi-camera scenario.
The results from all the cameras are projected to a common space and combined such that by result's refinement the individual detector performances are increased.
- (b) Increase people detection algorithms performance by the use of semantic constraining information to suppress false detections.

1.3 Thesis Structure

The master thesis is divided into the following chapters:

- Chapter 1. Introduction.
- Chapter 2. State of the Art.
- Chapter 3. Developed Application.
- Chapter 4. Proposed System.
- Chapter 5. Results.
- Chapter 6. Conclusions and Future Work.
- Bibliography.

Chapter 2

State of the Art

As explained in Chapter 1, the analysis of a public crowded space embraces many different algorithms from Computer Vision disciplines.

This Chapter aims to study the State Of the Art pedestrian detection approaches and how to improve these as it constitutes a pivotal field for our goals. In addition, it also covers the topic of contextual information and in concrete, semantic segmentation and its algorithms. Finally as both of these disciplines are used in a multi-camera setup, scenarios working with this configuration are also defined, presenting their advantages and disadvantages.

2.1 Pedestrian Detection

Pedestrian detection (PD) has been a major issue in computer vision during the past few years due to its relevance in all sort of computer vision applications. Its main objective is to detect and identify a potential object as a person by automatically detecting its position and relative size in the scene.

Nowadays, it can be considered a partially-solved problem. Although there are excellent pedestrian detectors in the literature, there is no algorithm able to effectively perform on a generic scenario. This is one of the reasons why PD is still one of the most researched areas in computer vision.

The complexity related to PD lies on the large amount of available data-sets with different video and people characteristics including challenges such as: people occlusions, different poses and scales and different illumination conditions. Caltech [12] (recorded on a vehicle in an urban environment.), ETHZ [13] (recorded from a chariot which moves through pedestrian paths), TUD [14] (static camera in a crossing campus scene) or INRIA [15] (collects precise people images both static and moving)

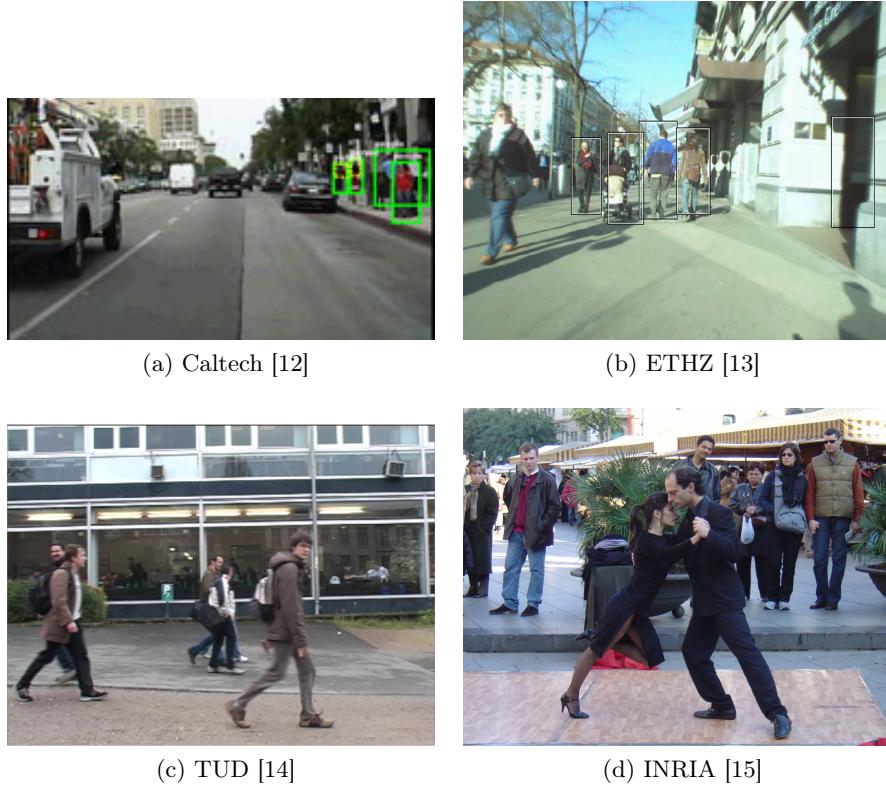


Figure 2.1: Image summary from data-sets.

are some of the many literature data-sets that have been used through the years to train different pedestrian detectors. Figure 2.1 gathers some examples that can be obtained from the different mentioned data-sets.

2.1.1 Pedestrian Detection Approaches

Some people detection approaches are presented through the following section. The PD State of the Art analysis is divided into three different classifications. Firstly, pedestrian descriptor and detection scheme is explained. Secondly, the person model and the algorithms to detect potential objects are analyzed. Finally, new trends in PD are briefly introduced.

2.1.1.1 Description and detection scheme

An organization of existing PD approaches based on the descriptor and detection scheme may start with the ones that use Histograms of Oriented Gradients (HOG) in combination with linear Support Vectors Machine (SVM) in order to describe

pedestrian shape with gradients to create a model and classify possible candidates [15]. Differently, Discriminative Part Models (DPM) such as [16] propose to divide the human body into different parts (head, trunk, legs...) and search for them into the image for a later combination into a single person detection.

Aggregate Channel Features [17] propose to use a combination of different channels such as normalized gradient magnitude, histogram of oriented gradients (6 channels), and LUV color channels in order to achieve the final detection.

2.1.1.2 Object detection and Model

In [18] an extensive evaluation of the state of the art of people detection is given. Here algorithms are characterized and differentiated from the others depending on the object detection approach and the used person model.

Object detection is defined as the extraction of the possible candidates to be a person from a scene. Mainly object detections algorithms are:

- Sliding window: -Also known as- exhaustive search leads to a classifier to test, in search of pedestrian, every possible image window. Parameters such as window size, or overlapping between them are common tuning values that increase or decrease the performance of the detector. These methods usually need from 10^4 to 10^5 windows per image and this number grows exponentially for multi-scale detection. If the complexity of the core classifier is increased in every window testing, the computational time will end up being not affordable.
- Segmentation: This line of research introduces segmentation as a preliminary step for PD. Algorithms such as background subtraction lead to moving parts of the image that generate interest objects from moving patterns. Others such as color segmentation are based on color skin to restrict the future people search only to those objects that fulfill the color condition. By all means, segmentation directly produces those scene candidates to be a person and so the computational time is highly decreased.
- Segmentation + Exhaustive search: Alternatively, a combination of both previously analyzed techniques. In this case the previous step of segmentation does not lead to final candidates but to a delimited small area that could contain some candidates objects. After the segmentation process a sliding window technique is performed over the reduced scene area and so, the final candidates are extracted. In this case improvements from both approaches are exploited as the computational cost of the exhaustive search (which is its main drawback) is

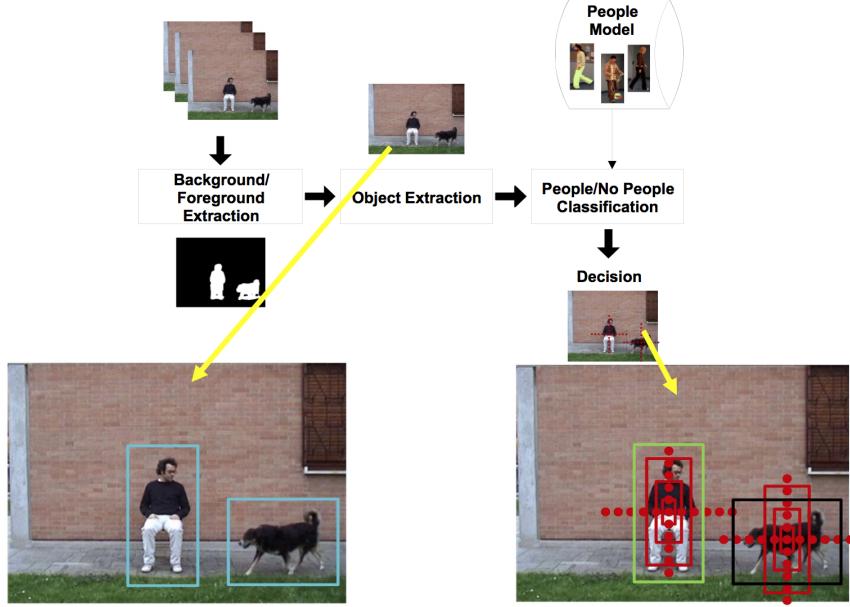


Figure 2.2: Generic Pedestrian Detector Example Diagram. Adapted from [18]

reduced by the use of segmentation. Figure 2.2 depicts a flowchart for a generic PD approach which relies on the combination of segmentation and exhaustive search.

The model of a person can be considered as the set of characteristics that are able to discriminate between people and any other object in the scene. In [18] three different kinds of person model are presented:

- Based on appearance: Most of the available detectors in the State of the Art use appearance information to define the person model. In this group of person models one can differentiate two approaches to describe the shape of a person.
 - ❖ Holistic: In these models people are defined as a unique and indivisible region or shape.
 - ❖ Part-based: These models however, rely on more complex characteristics where a person is defined as a combination of multiple shapes, regions or parts of its body.

Examples of appearance-based detectors are those that use silhouettes to classify people, either from an holistic or part-based basis, or color distribution in people. However the group of appearance-based PD is mainly covered with approaches based on the use of Histograms of Oriented Gradients like [15], Haar-like features

Video	HOG	ISM	Fusion	Edge	DTDP	ACF	Faster-RCNN
1	89.3	71.4	34.9	84.9	96.7	99.3	99.7
2	69.2	82.9	92.5	90.2	77.1	77.1	98.2
3	55.6	75.7	64.3	71.7	68.9	68.9	82.9
4	10.1	1.0	0.5	5.4	33.9	33.9	37.5
Average AUC	56	57.5	48	63	69.1	69.8	79.5

Table 2.1: Pedestrian Detection Performance. Adapted from [23] (selected approaches). Metric for this evaluation is the average AUC. This metric measures the area under a Recall Over Precision curve. See [VPU Website](#) for the complete table.

[19], or combination of multiple features and aggregate channel features -e.g. the ACF [17] which combines HoG, gradient and color information-.

- Based on motion: Human appearance is likely to change due to environmental factors such as light conditions, cloths or camera settings. In addition, people variability in terms of height, weigh and poses make appearance likely to vary. For these reasons, some approaches try to get rid of these factors and detect pedestrians using only its motion information. In [20] detections are based on periodic motion analysis. The algorithm performs motion segmentation and tracking to later on compute the self-similarity between objects.
- Based on appearance + motion: Algorithms such as [21, 22] merge both appearance and motion approaches in order to improve results. Most of these algorithms combine people detection and tracking, and so, they have been designed to improve people tracking over video sequences rather than to outperform State of the Art pedestrian detectors.

In [23] a comparison of the performance of PD on different data-sets is made. This comparison derives to a ranking which is partially included in Table 2.1.

2.1.1.3 Recent Trends in Pedestrian Detection

However, last years a new scheme of detectors have started to being used. Detectors based on deep Convolutional Networks have improved notably the accuracy of all the previous analyzed algorithms. Examples such as ImageNet [24] for image classification and Faster R-CNN [5] for object detection expose that deep convolutional networks usually improve the performance of aforementioned approaches. This fact is clearly presented Table 2.1 where Faster R-CNN outperforms every other approach.

2.1.2 Object Proposals

Described PD such as HOG, DPM or ACF utilized the analyzed “sliding window” algorithm, however, as mentioned before one of the main drawbacks of this approach is the final computational time needed to achieve good performance results.

One of the most successful solutions to overcome this time consumption problem without losing detection quality is the use of object proposals [6].

Object proposals approaches perform a complete search over an image to detect potential object candidates. These candidates are detected as image areas with visual properties that distinguish them from the scene background.

In general, object proposal approaches reduce pedestrian candidates respect to sliding-window like algorithms. Leading to a higher object recall and increasing the efficiency of the detection process. Successful examples of using proposal to improve and speed-up detection include the aforementioned ImageNet [24] and Faster R-CNN [?].

In [6] three set of proposal methods groups are proposed and analyzed:

- Grouping proposal methods attempt to generate multiple, and so, overlapping segments that are likely to correspond to objects. Here one can distinguish between three types of methods according to how they generate proposals. Methods can generate proposals by groping super-pixels (SP), solving multiple graph cut (GC) problems or finally, using edge contours (EC). Among those that use SP we can find Selective Search [25], Randomized Prim’s [26], Rantalankia [27] or Chang [28]. Those that use GC are CPMC [29], Endres [30] or Rigor [31]. Finally Geodesic [32] and MCG [33] use EC to obtain proposals.
- Window scoring proposal methods are an alternative approach to score each candidate window according to the probability to contain an object. Usually this methods tend to be faster and, in addition, they typically extract only bounding boxes. One can find among other approaches Objectness [34], Rahtu [35], Bing [36], EdgeBoxes [37], Feng [38], Zhang [39], RandomizedSeeds [40].
- Alternative proposal methods. Apart from the main groups a set of alternate approaches such as ShapeSharing [41] or Multi-box [42] are also used to extract object proposals.

2.1.3 Next Steps Towards Generic PD

As said before PD is constantly in development and so, some future work lines can be set. In [3] some research directions are proposed that could be of interest in the

scope of this work.

1. Context information should be added. Starting from the hypothesis that a person should be placed on the floor, the ground plane assumption can reduce errors if the detection for both the person and the floor are accurate. This could be achieved by extracting useful contextual information from the scene. This is one of the main objectives of the work.
2. Occlusion treatment. Usually pedestrians, due to other scene elements such as columns or even other pedestrians appear occluded. When this happens PD performance is substantially degraded under even mild occlusions. Improvements in this area could increase the performance in real life situations.

2.2 Contextual Information

One can describe contextual information as the set of additional circumstances or facts that one can extract from a scene besides the target of analysis. Generally, this set of circumstances is a wealth of information that is not extracted by the image analysis but extracted by humans based on previously acquired knowledge during their life. By just taking a look to an outdoor image a human can derive where the sky will be, what the weather conditions are or which time of the day is. Also, by knowing the place the photo was taken, one would imagine which objects are more or less probable to appear in the scene.

Dealing with computer vision disciplines, contextual information sources also include camera information (such as position, configuration, distance to an object and camera motion), as well as set of objects that one could detect in the scene or how many views are available.

All this set of information that is not extracted from the image analysis provides a more general understanding about the scene and helps with further algorithms. We can divide contextual information into two different levels: global and local contextual information. Besides, we can also further divide contextual information into two different categories offline, and online. Finally, semantic information is also analyzed.

2.2.1 Global

Global context considers image detections from the image as a whole. For instance, if the context of a scene is known -kitchen-, we can use this information to search for typical objects in this context -e.g. a stove-.

This kind of approaches are focused on psychology studies that suggests that human perceptual processes work following a hierarchically organized process [43, 44]. Our perception system goes from a global structure towards a more detailed analysis in a top-down scene interpretation.

Global context approaches aim to define a scene as an extra source of global information. The structure of a determinate scene image can be estimated by means of global image features [45].

2.2.2 Local

On the contrary, local context refers to contextual information related to an object, e.g. a kitchen table may help predict the presence of a spoon.

The impact area of an object -in contextual terms- is defined as a set of other objects, patches or even pixels. Algorithms dealing with the extraction of local contextual information aim to correctly define the area that surrounds an object to precisely detect other object instances.

2.2.3 Offline

Offline contextual information is defined as the set of circumstances that are computed before starting any kind of analysis procedure. This information leads to external image information that is used to constraint analysis algorithms. Approaches such as [18] uses previously introduced contextual information to improve part-based pedestrian detections over a scene.

2.2.4 Online

Online information, on the other hand, is computed with the analysis. Online extraction entails a degradation of an algorithm efficiency, albeit allows to dynamically update the context.

Examples of online (and local) contextual information extractors are the algorithms in the semantic segmentation branch. Next section (2.2.5) discuss some of the approaches in this vein.

2.2.5 Semantic Segmentation

Semantic information is defined as the set of high-level elements from contextual information. This can often lead to characteristics such as global image color [46]. It can also describe an image by the position and status of relevant objects [47]. Or it

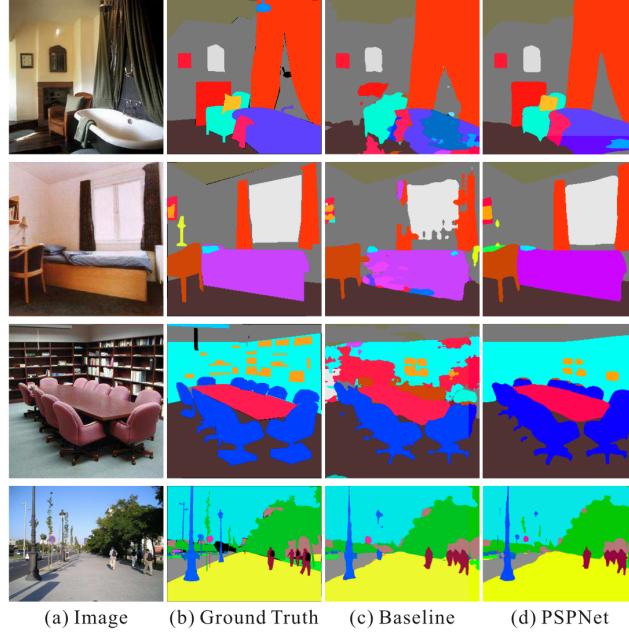


Figure 2.3: Scene parsing on ADE20K data-set [48]. Adapted from [7].

also defines concrete image areas in a scene such as walls, corridors or walking paths [7].

In other words, semantic segmentation has the goal to assign each image pixel a high level category label. If accurately done, it provides complete semantic understanding, which in terms of computer vision, means that location of an object within an image will be known. The result of semantic segmentation is depicted in Figure 2.3, where scenes are analyzed and divided into separate semantic areas.

Semantic segmentation is a recent trend and nowadays, it remains a significant challenge for the computer vision community. Due to its short-life term there is not yet a complete survey available in which algorithms are deeply analyzed and compared. However, there are a set of benchmark suits where developers can upload their obtained results with a given dataset and so, algorithms performance can be compared.

An example of benchmark is Cityscapes Data-set [49]. It is a large-scale data-set that contains stereo video sequences recorded in street scenes from among 50 different cities around the world. This data-set presents class annotations over pixels in more than 5000 frames. This set of categories and classes are presented in Table 2.2.

In Table 2.3 we can observe an adapted version from [Cityscapes Website](#) in which some of the most accurate algorithms are presented. Only those algorithms that have more than 80% on IoU class metric have been mentioned in this thesis for practical

Category	Classes
Flat	road · sidewalk · parking · rail track
Human	person · rider
Vehicle	car · truck · bus · on rails · motorcycle · bicycle · caravan · trailer
Construction	building · wall · fence · guard rail · bridge · tunnel
Object	pole · pole group · traffic sign · traffic light
Nature	vegetation · terrain
Sky	sky
Void	ground · dynamic · static

Table 2.2: Cityscapes Data-set Class Definitions

Algorithm Name	IoU Category	IoU Class	Available Code
motovis (Anonymous)	91.5	81.3	No
PSPNet [7]	91.2	81.2	Yes
ResNet-38 [50]	91.0	80.6	Yes
NetWarp (Anonymous)	91.0	80.5	No
TuSimple_Coarse [51]	90.7	80.5	Yes

Table 2.3: Cityscapes Data-set Challenge Results (Intersection over Union metric)

reasons.

PSPNet, ResNet-38 and TuSimple_Coarse are all based on convolutional networks. This fact reveals that deep convolutional neural networks (CNNs) have led to significant improvement over previous semantic segmentation systems since the presentation of AlexNet [24] in 2012.

However, even when using CNNs the main difficulty of scene parsing is related to the type of scene and to label variety.

PSPNet deals with this problems assigning relationships between different labels, i.e. an airplane is likely to be in runway or flying in the sky while not over a road or in the water. This relationships reduce slightly the complexity of having large amounts of labels to predict and improve the general performance of the algorithm.

ResNet-38 on the other hand, propose not only to not increase CNNs depth, but rather to ensemble many relatively shallow networks to increase performance. Their

approach also improves usability reducing memory use and sometimes even training time.

Finally, TuSimple_Coarse propose a combination between dense upsampling convolution (DUC) to generate pixel-level prediction and a hybrid dilated convolution (HDC) framework.

In Figure 2.4 some visual examples of how this algorithms perform on Cityscapes Data-set frames are displayed.

2.3 Multi-camera scenarios

The use of various cameras is a common setup when dealing with video surveillance problems. One can define as a multi-camera scenario one space that has more than one video camera recording. Ideally, the recordings for the different cameras are temporally aligned -synchronized-. Having N multiple camera instances allows to observe the same event or object of interest from at least two different points of view. This leads to a set of advantages in the scope of our work when dealing with PD and semantic classification and also, to some unavoidable disadvantages.

- Advantages

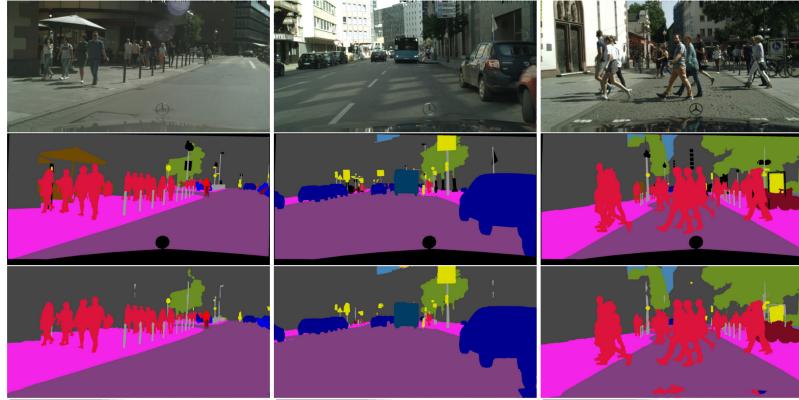
As said in Section 2.1 one of the main research paths in PD is the occlusion treatment. In this case, the use of a multi-camera scenario with computed homographies between camera frames could help. This could be achieved by reprojecting detections from one camera to another whose miss rates are high [52].

When talking about semantic segmentation the inclusion of a multi-camera system could arise some benefits. While a single-camera system could lead to misclassification of labels in the image or even to represent an object with many classes due to for example, camera capture problems, in a multi-camera system one camera instance could help to refine the classes in another one provided that, evidentially, they are analyzing the same common area [53].

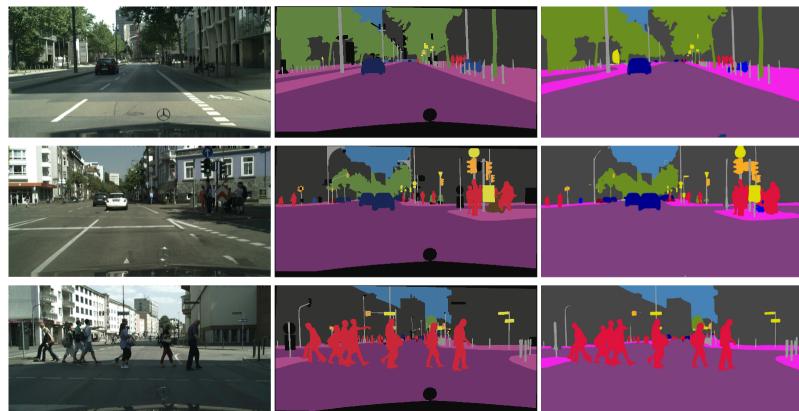
- Disadvantages

The main disadvantage when dealing with multi-camera systems is the exponential grow of computational time. Algorithms should be performed N times. This issue could be solved by the use of parallel coding that perform cameras processing simultaneously.

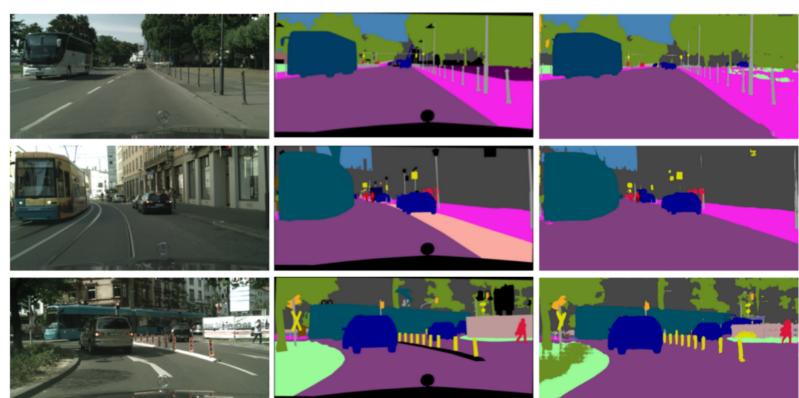
Besides, the use of multiple cameras entail two additional tasks: the temporal



(a) ResNet-38 Algorithm. From top to bottom: Input images, ground truth and results.



(b) PSPNet Algorithm. From left to right: Input images, ground truth and results.



(c) TuSimple_Coarse Algorithm. From left to right: Input images, ground truth and results.

Figure 2.4: Semantic Segmentation result examples on Cityscapes Data-set.

alignment of the views -synchronization- and the spatial arrangement of the different view -homographies-.

Chapter 3

Developed Application

Within this Chapter the developed application in terms of software development will be analyze. This application will be the base for the calculation, visualization and arrangement of the usage statistics from the different areas of interest, pedestrian detections and other results. As said in Section 1.2 this usage data can be pre-generated or generated ideally under a real-time constraint. The main application environment should be user-friendly to ensure a correct and easy usage by the end user. It has been developed completely from scratch for the purpose of this Master Thesis.

The application has been developed under [QT Creator](#) coding environment in Mac OS Sierra. This decision has fundamentally been based on the following QT characteristics:

1. Its cross-platform characteristic which makes it easily portable from one operating system to another such as Windows or Linux distributions.
2. Its application window designer that enables the programmer to design software windows by using an interface instead of having to code to create the mentioned window and set up all the desired configuration (Figure 3.1).
3. The possibility to add OpenCV libraries to the project as well as independent external libraries.
4. Its multi-thread capabilities that enables to perform different code segments in various threads to increase computational speed.

Due to the complexity of some of the algorithms used in terms of parameter tuning and configuration two separate applications have been developed, engineer and user version.

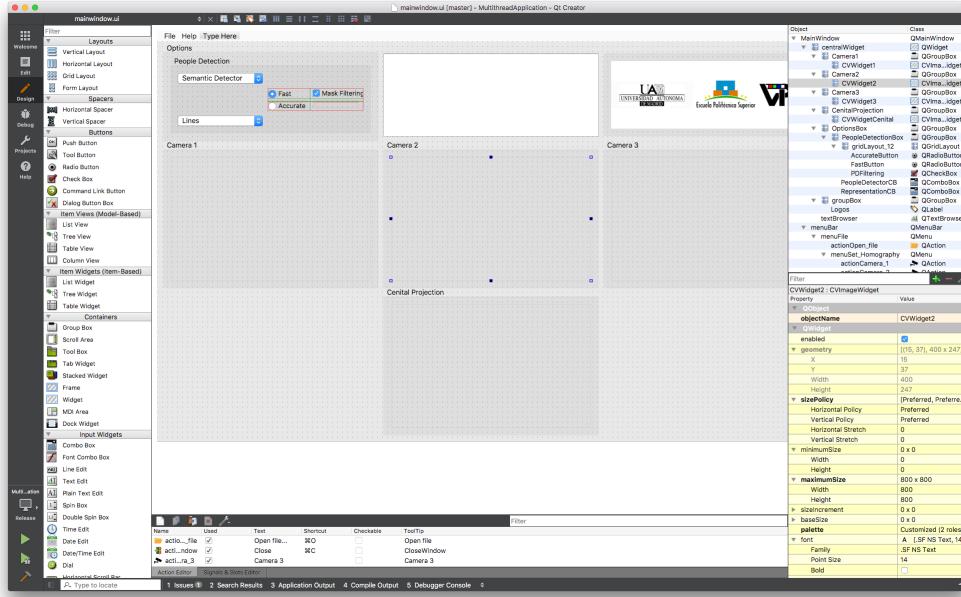


Figure 3.1: QT Main Window Designer

The first version of the software corresponds to the engineer application. As its name says, it is design so it can be used by programmers or engineers who generally understand concepts of the algorithms running at the backend application. This means that all the variable parameters are available for tuning from the graphical interface, as well as different detector options and visualization.

The final motivation for this version is to achieve high variability and tuning in terms of algorithm parameters, however, in order to have good performance the user should have basic knowledge about how parameters are affecting the software performance.

For the engineer application both single-thread and multi-thread versions have been developed and are analyzed on the following lines. All the code for both approaches is available in the following [GitHub Repository](#).

During the analysis of the application trough out the Section some flow-charts are displayed. The used legend in those can be observed in Figure 3.2.

3.1 Single-thread Engineer Application

During the first stages of the development and for simplicity sake the application has been design and developed to run under a single thread. This means that all the processing has been done sequentially camera by camera. A simple flow-chart

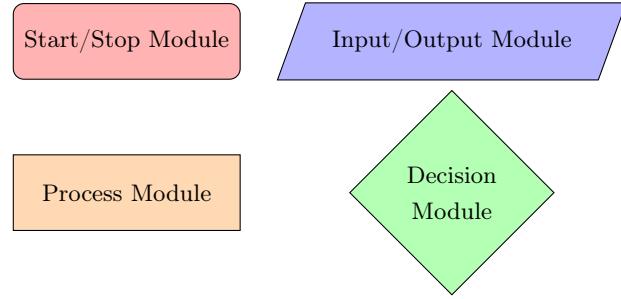


Figure 3.2: Flow-chart legend

diagram that illustrates the execution path can be seen in Figure 3.3 .

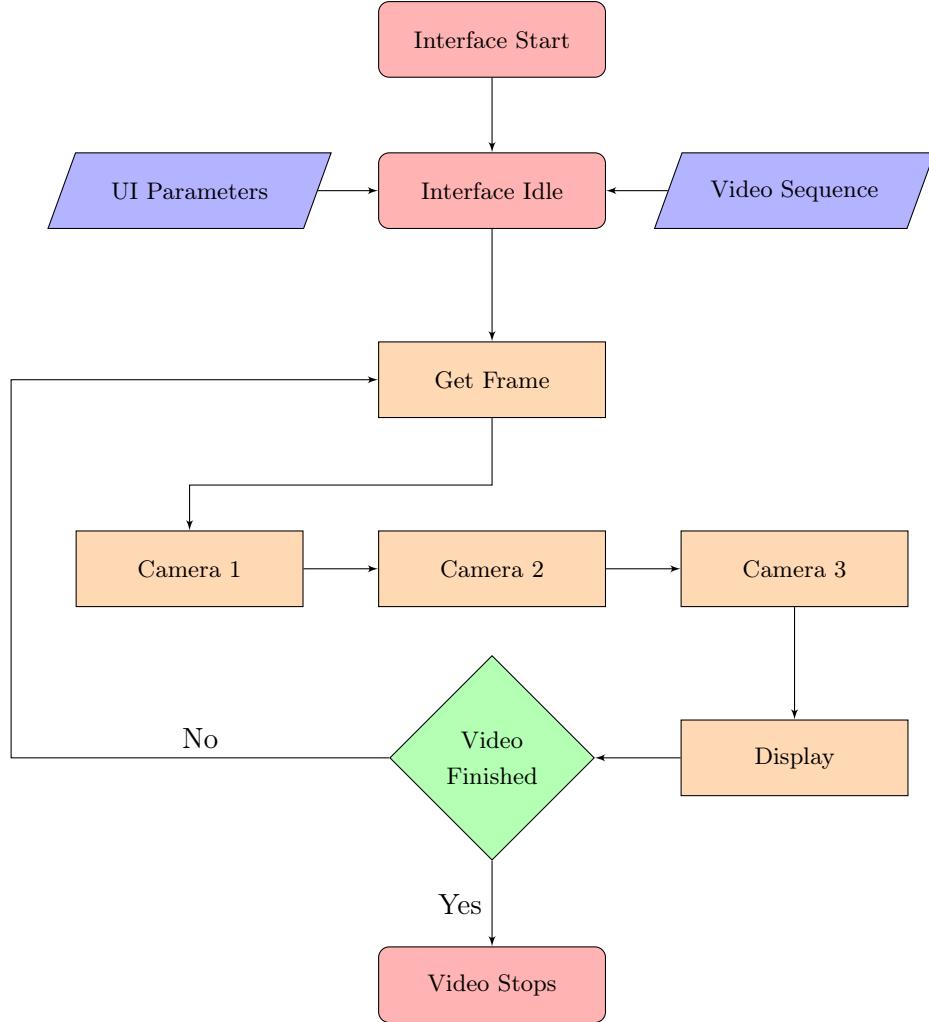


Figure 3.3: Flow-chart diagram for the single-thread application.

This approach has the advantage that all the code is executed in the same seg-

ment which makes really easy for instance, to share information between cameras as they share the same memory segments, however, this design will only be valid if the computational effort is minimum. Before displaying any results, all the process for the three cameras should be computed one after the other. This means that when calculating detections for one camera the others will remain idle. When working with such a multi-camera system with heavy algorithms running as the proposed in our work, the computational time increases exponentially and this design is no longer worthwhile.

3.2 Multi-thread Engineer Application

The new and used approach can be observed in the flow-chart displayed in Figure 3.4. As one can observe, now different threads are running in parallel, one for each camera, and so, all the process is no longer done sequentially and computing power from the CPU can be much more usable.

Now, however, as threads are running separately one have to create some sort of synchronization between them to keep consistency in the application. One thread can process a frame faster than another one due to multiple external reasons, nevertheless, the application should display the same exact frame for all the cameras more over if the information is going to be shared between threads. In our case the synchronization is perform by the barrier that can be observed in diagram 3.4. This barrier will create a meeting point for all the threads that all of them must reach before continuing with their execution.

In the code two barriers will be available. The first one will ensure that all the threads have perform pedestrian detection before sharing those detections between the rest of the threads. The second one will be at the end of a frame execution, so threads wait to each other before sending results to the main window for representing processes.

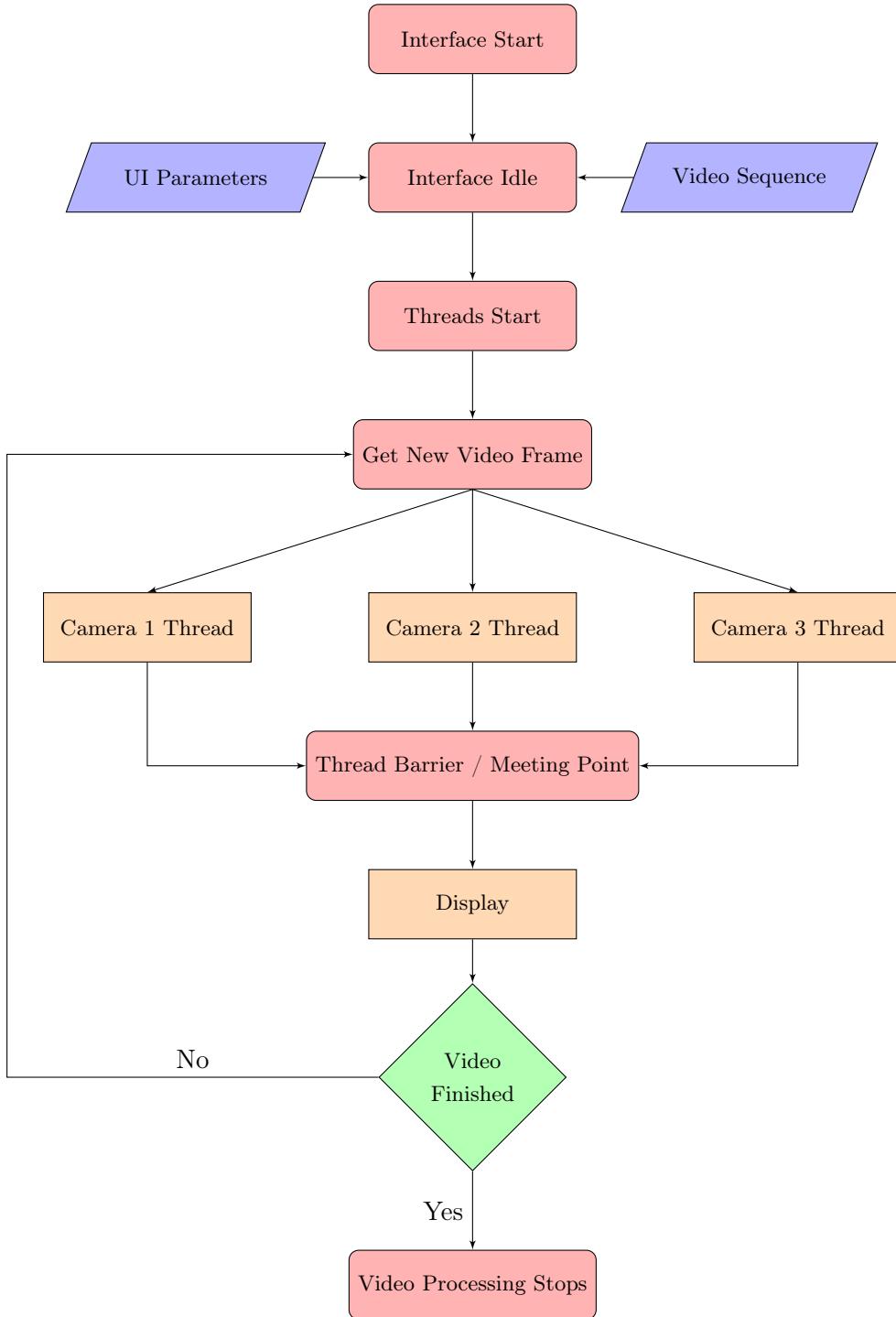


Figure 3.4: Flow-chart diagram for the multi-thread application.

Main application window is shown in Figure 3.5. As one can observe it is composed of four separate areas:

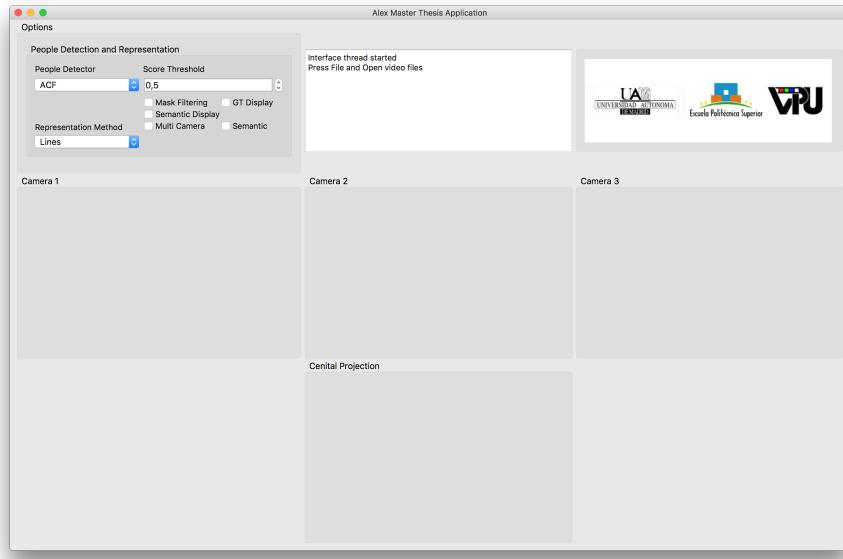


Figure 3.5: Main application window.

1. Application menu bar.

In this menu we will have the main application actions. From here the user can open a new video sequence, compute the set of needed homographies for the algorithms or close the program. The application also provides a help searcher and an external information window. This set of functions can be seen in Figure 3.6.

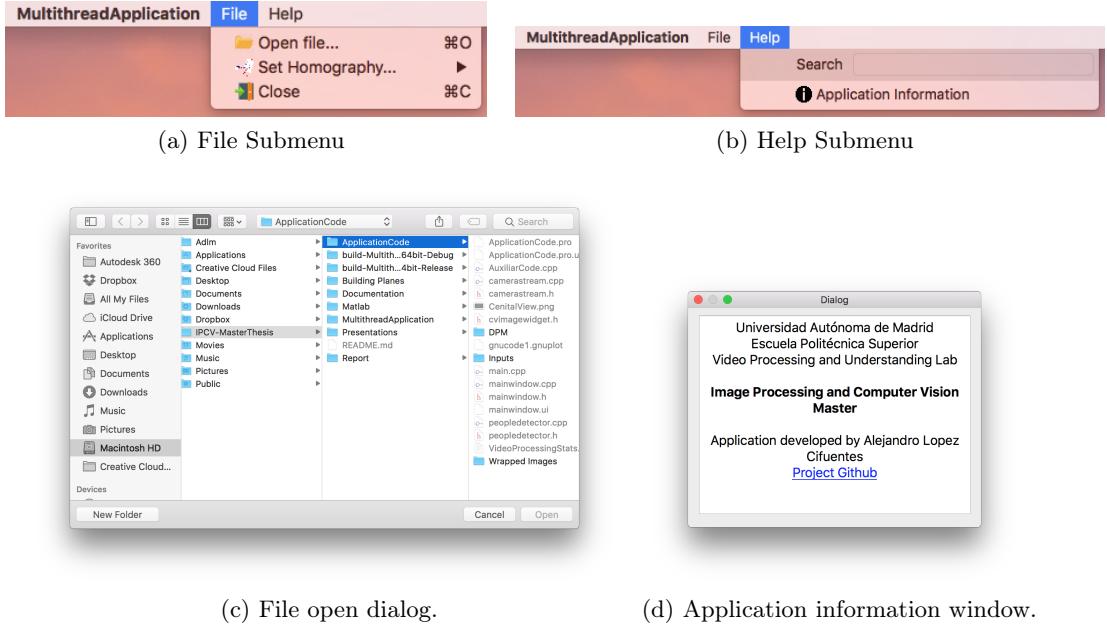


Figure 3.6: Application menu bar

2. Options menu.

The options box (Figure 3.7) in the application will contain all the possible parameters that can be tuned during the execution of the program. From here algorithms can be changed in real time so there is no need to restart the running before changing some parameter. The user can select among various pedestrian detectors such as PSP-Net detector, DPM, ACF or even Fast-RCNN as well as the type of representation that one wants for these detections, lines or gaussians which will be explained in Section 4.3.2. It also enables the user to select the desire pedestrian detection threshold as well as the filtering or constraint that is used. One can select between regular pedestrian detection, PD with semantic constraining or to perform multi camera projection. In addition mask filtering can be also perform so PD search area is reduced. Finally, a check box to display or not ground truth information is available too.

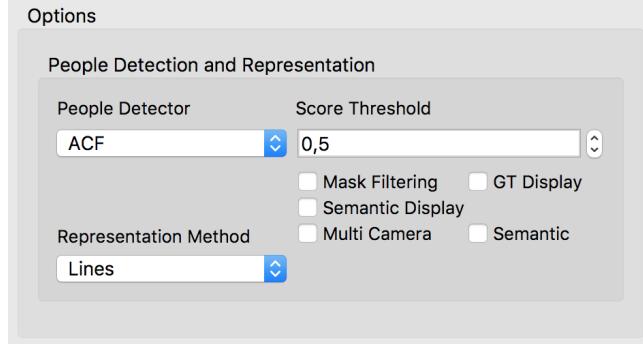


Figure 3.7: Options Menu.

3. Information Display

Along this text box some guide information will be provided to the user. Messages such as “Open video files”, “Processing starts now” or “DPM Pedestrian Detector is now in use” will appear during the execution of the application so the user can obtain some information about what to do, or what algorithm is in use. This can be observed in Figure 3.8.

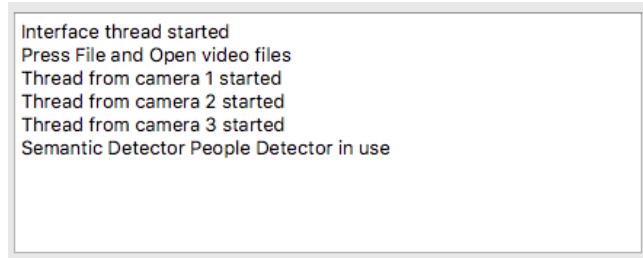


Figure 3.8: Information Display

4. Results Display

This is the main display area in the application in which all the visual results are presented. We have three separate windows for each of the used camera as well as one more display window for the cenital plane. Here the camera frames with its pedestrian detection or/and ground truth will be shown and all the projected semantic can be observed on the cenital frame. An example of its performance is presented in Figure 3.9.

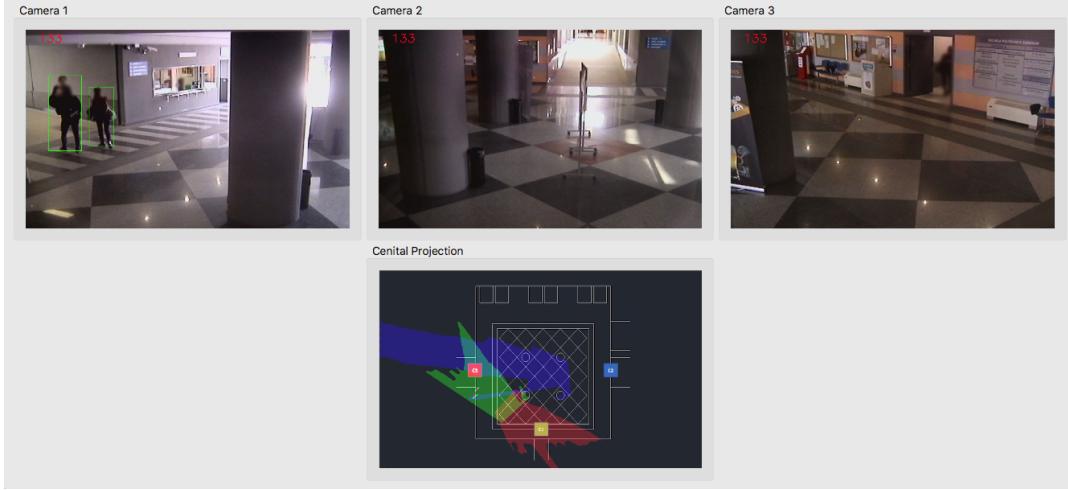


Figure 3.9: Results Display Area

3.2.1 Classes Distribution

In terms of C++ blocks the application has been divided into several classes for a better code design and easier understanding. Their functions will be explained in the following lines:

- MainWindow. This class corresponds to the main interface window and main application thread. It is the base for all the further processing as everything will be inherit from this class. The functions that are done by this class are creating file open dialogs, setting up and start all the camera threads, update all the algorithms configurations with values from the UI and displaying results through the CVImageWidget class. It is also responsible of the information sharing between threads.
- AboutWindow. Class that execute the second available information window. This instance will display general information about the application and its developers.
- CameraWorker. Main class for all the execution in each of the cameras. CameraWorker class is linked with a unique thread that will process all the algorithms inside. It has CameraStream, PeopleDetector, Evaluation and Barrier classes declared within it to distribute the processing.
- CameraStream. This class will perform all the functions that has to deal with the video processing except pedestrian detection. The main reading loop, homographies and semantic projections are computed in this class.

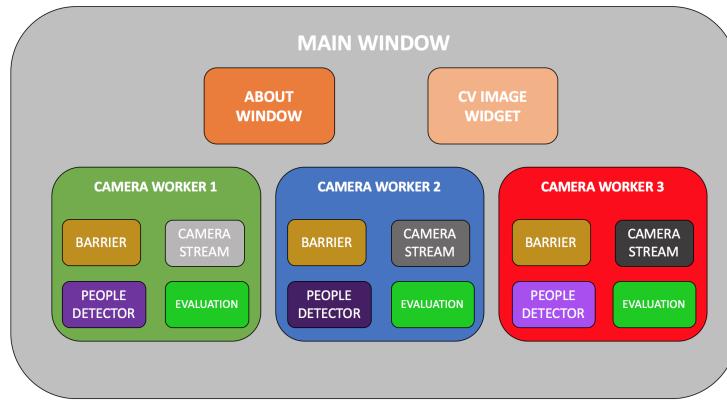


Figure 3.10: Hierarchical representation of the code.

- **PeopleDetector.** Main class to perform everything with respect to pedestrian detection. All the algorithms to detect, project and draw pedestrian either on the camera frame or the cenital plane are from this class.
- **Evaluation:** Here ground truth is read and also the evaluation between system pedestrian detection and ground truth information is performed.
- **Barrier.** This class implements everything that has to deal with thread synchronization. It is declared in Main Window and passed by arguments to the thread so each of them has the same exact barrier to perform the synchronization.
- **CVImageWidget.** Display representation class that deals with all the process to finally paint OpenCV Mat images into a QT main window interface Widget.

In Figure 3.10 a hierarchical representation of how the different classes are related in the code is presented. As on can observe everything is under the heritage of the main window. Here we have the three camera worker threads which have inside the same barrier, and each of them a camera stream, a people detector and a evaluator. In addition, main window will also be the parent of the extra about window and the CVImageWidget.

3.3 Multi-thread User Application

On the contrary to the analyzed version, the second developed application is focus on general users. This version only allows to load the video files and display results. All the parameters are set by default so the user does not have to fine tuning any of them making the usage and the general perception of the application much more

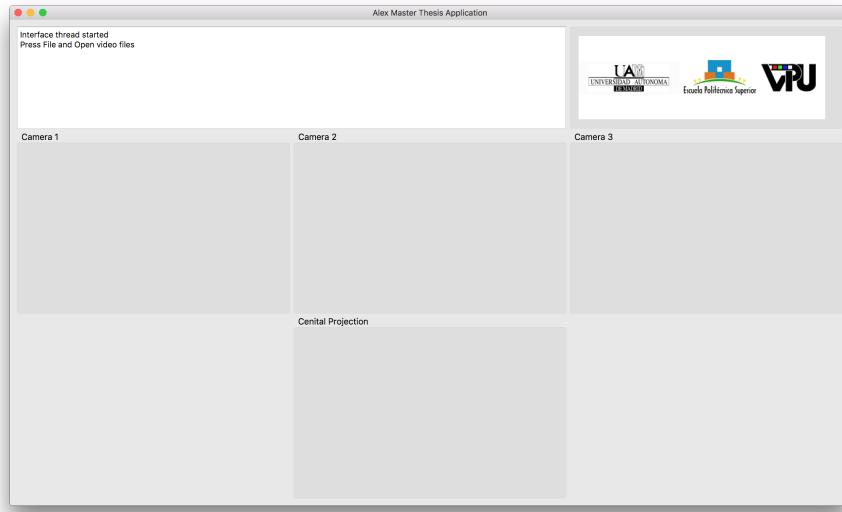


Figure 3.11: User version application main window.

simple and easy. This method ensures that achieved results are the best ones that the proposed system can obtain and it is the best approach to display demos.

Figure 3.11 displays the general application window where we can observe the difference with the Engineer version.

As said, conversely to the engineer application the only functionality of the main window is to display results and guide information. All the options presented in the engineer application for tuning are no longer available.

Chapter 4

Proposed System

During this Chapter our proposed system is deeply explained. We start from the main contextual model generation and pedestrian detectors to finally explain the fusion of all the obtained elements in a multi camera system with semantic constraints. In addition the generation of statistical usage data from semantic areas is proposed. Figure 4.1 represents the flowchart that the application follows for the computation of the main mentioned algorithms.

4.1 Contextual Model Generation

One of the main objectives in the scope of this work is to perform semantic segmentation, which as explained in Chapter 2 means to divide one frame into different semantic areas. The relative position in the scene for elements such as doors, walls, paths, and columns are necessary to achieve further objectives such as multi camera pedestrian constraint and statistical data extraction. For this complex task the algorithm PSP-Net [7] presented in Chapter 2 is used. We choose PSP-Net because at the moment of this work was the one with available code achieving the best results. The goal for this algorithm as said before, is to assign each pixel in the image a category label achieving by this the location and shape for each element.

This process is based on a deep Convolutional Neural Network (CNN) called Pyramid Scene Parsing Network (PSPNet) which is designed to improve performance for open-vocabulary object and stuff identification in complex scene parsing. The structure of the network can be observed in Figure 4.2.

Given the image in 4.2.(a) the first step is to process it through a pre trained CNN called ResNet [54] to get the full feature map 4.2.(b) of the last convolutional layer. The final feature map in this step is 1/8 of the size of the input image.

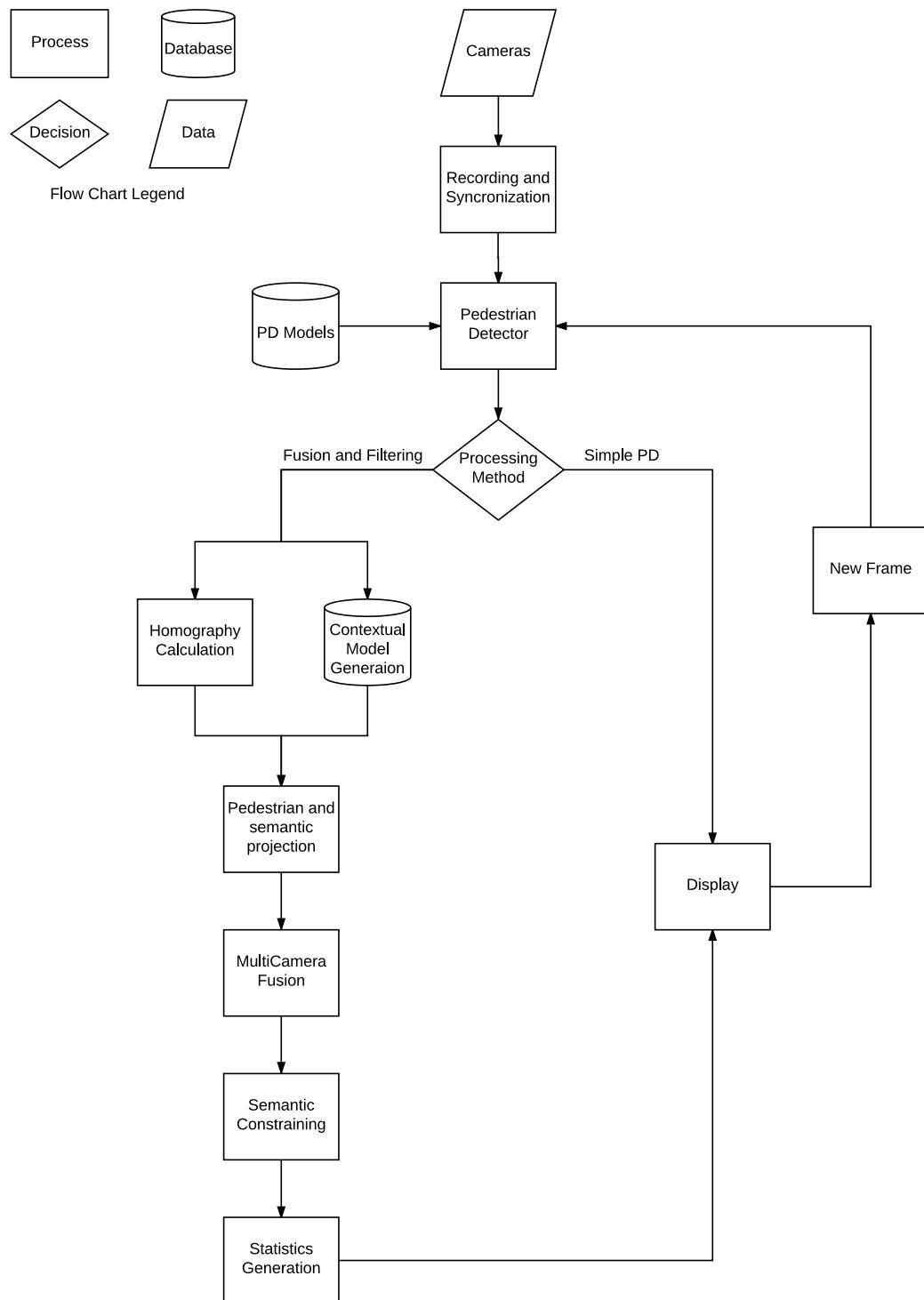


Figure 4.1: Proposed system flowchart

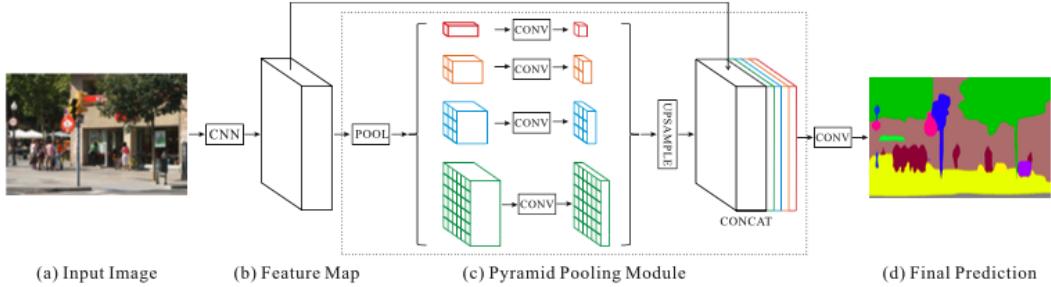


Figure 4.2: Overview of the proposed PSPNet

The second step is to apply the main contribution of [7], which is called the Pyramid Pooling Module 4.2.(c). The main objective of the module is to collect a few levels of information, much more representative than global pooling. It separates the feature map into different sub-regions and forms pooled representations for different locations. Here a set of pooling, convolutional and upsampling layers are applied to harvest different sub-region representation in N different scales.

After the bilinear interpolation upsampling, concatenation layers are used to form the final feature representation by fusing the feature map extracted in 4.2.(b) and the Pyramid Pooling Module output. This final feature carries both local and global context information. In the end, the representation is fed into a convolutional layer which gets the final per-pixel prediction 4.2.(d).

PSP-Net comes with a set of three different pre trained *Caffe* models for three different datasets. The main difference between the models for our scope is the environment in which the network has been trained.

- ADE20K: This dataset is the most challenging as it has up to 150 different labels in a wide range of scenes. The scenes go from interior room places to outdoor scenarios.
- VOC2012: It contains 20 object categories and one background class from diverse indoor and outdoor scenes.
- CityScapes: The last dataset defines 19 categories containing both stuff and objects. All the available sequences have been recorded from a driving car while driving in the street.

As one can observe the three different models represent different object categories in different real spaces. In our case we select the model based on two main reasons:

1. The model should have been trained with indoor scenes. This leads to discard those models that represent only outdoors scenes as we would like our approach

wall	building	floor	ceiling	road
window pane	person	door	table	chair
seat	desk	lamp	column	counter
path	stairs	screen door	stairway	toilet
poster	bag			

Table 4.1: Final classes list from ADE20K to use in PSP-Net

to be used in an interior scenario. This will exclude CityScapes dataset from our options as all the classes and sequences used for training are from outdoor scenes.

- From the trained indoor models we have to choose between those whose categories best fit in our work. In this case VOC2012 dataset uses classes such as boat, airplane or table which are not interesting for our segmentation problem and it does not have classes such as door or wall which are really important for us.

With this two reasons being taken into account we have selected the model ADE20K because as said, it has elements such as walls, floor, person and column in its model. However, we consider that most of the 150 label categories will be unused in our procedure, so, the number of classes from the model has been reduced to the 21 classes of our interest. Position and scores for those objects are the only ones obtained. This class limitation leads above all in a considerably hard drive space saving. In Table 4.1 the final 21 selected classes are exposed.

4.2 Pedestrian Detection

Along this section pedestrian State of the Art detectors that have been selected to work in our system are presented. Some of them have been chosen due to algorithm simplicity and computational cost and others, due to its contrasted performance while working in real sequences as we have seen in Chapter 2. However, one of the main reasons of choosing the following five algorithms among others in the SoA is the possibility of either having the original source code or the practical implementation within an external OpenCV library.

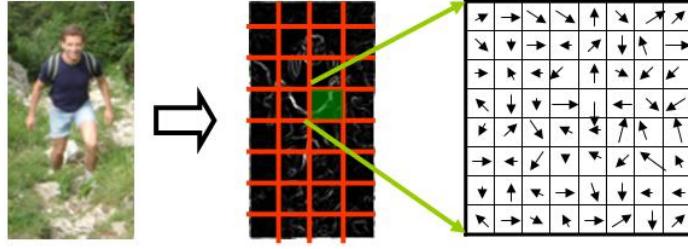


Figure 4.3: HOG Pedestrian Descriptor

4.2.1 Histogram of Oriented Gradients

Histogram of Oriented Gradients, i.e. HOG, is one of the main used detectors along pedestrian detection field. This fact is due to it's extremely simplicity in terms of the descriptor complexity. Pedestrians are described as set of HOG. This means that its shape and appearance can be described by a set of gradients and intensities organized as orientation histograms. These histograms describe intensity distributions from local gradients or border directions. This descriptor can be observed graphically in Figure 4.3.

Once HOG have been used to describe the person shape, Support Vector Machines are used to train a person model and to classify potential candidates as people. SVM are a data classification method formed by a set of supervised training. The aim of this kind of approaches is to produce a model which is able to predict classification labels on a test set based only on the descriptors of the set and the model.

The idea behind SVM is that training vectors are mapped on to a bigger dimensional space in which the data separation, by means of one or many hyperplane, is much easier to divide than in the original dimensional space.

The combination between HOG and SVM leads to a fast detector that depending on the situation will perform decently, although it has some main drawbacks as its lack of occlusion treatment which does not make this algorithm usable when working with crowded spaces.

The main implementation of Histogram of Oriented Gradient Pedestrian Detector is in OpenCV library for C++.

4.2.2 Deformable Part Model

As was mentioned in the previous paragraph one of the main drawbacks when working with the simple HOG pedestrian detector is that it describes the person model as a hole which leads, inevitably, to the mentioned occlusion drawbacks. Deformable Part Model tries to solve this problem, among others, by defining the model as first, a

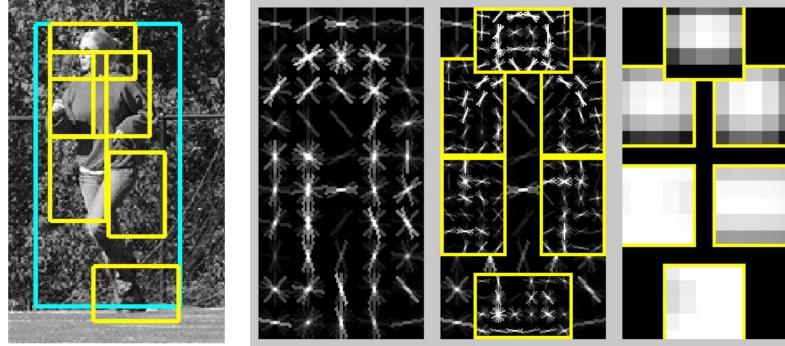


Figure 4.4: Example detection obtained with the DPM person model. From left to right: Original image + detections, global coarse model, part templates and spatial model for each part. Image extracted from [4].

global coarse template, secondly, several higher resolution part templates and finally a spatial model for the location of each part. This description is the one that can be observed in Figure 4.4.

Both global and part templates are modeled with histogram of gradient features and the model is built by using an improving over SVM called latent SVM. In addition, scores for every detection are obtained by applying a root filter on the window plus the sum over parts of the maximum over placements of the part filter score on the resulting sub window minus the deformation cost.

The use of this detector leads to a set of advantages than when working with others simpler approaches. In terms of pedestrian occlusion treatment we are able to detect those people that have been occluded by something in the scene just by detecting some visible part. This outperforms other detectors while working with crowded scenes in which holistic methods have problems that lead for instance to groups of people being detected as a unique detection while DPM is ideally able to separate them into different person instances.

However, its scanning window approach as well as the part based model lead to some computational cost that will increase the time needed to obtain detections.

The main implementation of Deformable Part Model Pedestrian Detector can be found in OpenCV library for C++.

4.2.3 Aggregated Channel Features Detector

The basic idea behind ACF detector is to increase other approaches performance by the use of many different channels to describe an input image I . In Figure 4.5 one can observe the working path of the mentioned detector. Given an initial image I , several

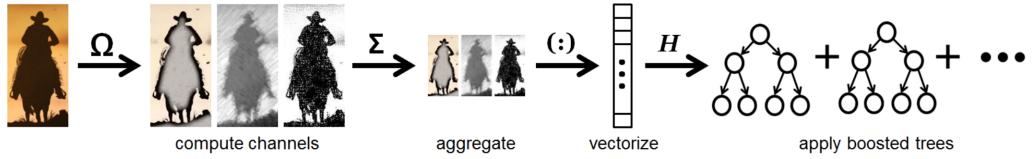


Figure 4.5: Aggregated Channel Features architecture. [17]

channels are computed. These channels are named $C = \Omega(I)$. After the computation, every block of pixels in C is summed and the resulting lower resolution channels are smoothed. After a vectorizing process features are single pixel lookups in the aggregated channels. Boosting trees are then used to learn these features (pixels) in order to distinguish people from the background. It is quite evident that the use of the correct channels leads to better results. In [17] a set of 10 channels are used to achieve state-of-the-art performance in pedestrian detection:

1. Normalized gradient magnitude (1 channel).
2. Histogram of oriented gradients (6 channels).
3. LUV color channels (3 channels).

4.2.4 Fast Region-Based Convolutional Network

Fast Region-Based Convolutional Network (Fast R-CNN) is used to perform offline pedestrian detection in our proposed system, however, as said in Chapter 2 it is not only a pedestrian detector but an algorithm for object detection. In 2.1.2 we mentioned that Fast-RCNN must use object proposals for its usage. In our developed system MCG [33] grouping method is used.

Fast-RCNN method sets its contributions in a several number of innovations to improve training and testing speed over its fundamental base R-CNN:

1. Higher detection quality (mAP).
2. Training is single-stage, using a multi-task loss.
3. Training can update all network layers.
4. No disk storage is required for feature caching.

In Figure 4.6 one can observe the general Fast R-RCNN architecture. The input for the Fast-RCNN network are the entire desired image that one wants to process and the set of object proposals. The first step in the network is to process the whole image

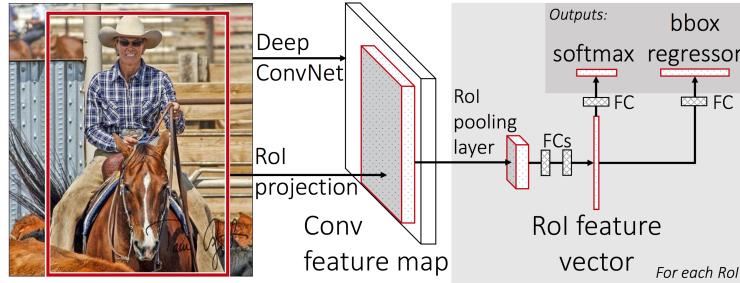


Figure 4.6: Fast R-RCNN architecture. [55]

with several convolutional and max pooling layers to produce a convolutional feature map. Then, for every object proposal present in the image, a region of interest (ROI) pooling layer extracts a fixed-length feature vector from the feature map.

Each feature vector is after, introduced into a sequence of fully connected (FC) layers that finally diverge into to output layers. The first one produces probabilities estimates over K object classes. The second one outputs four real numbers for each of the K object classes. This set of 4 values encodes the final bounding-box positions for one of the objects from the K classes.

In this case, both Fast-RCNN detector and MCG object proposal extract are implemented within external Matlab libraries and so, should be computed offline and introduced externally to the application.

4.2.5 PSP-Net

As we explained in Section 4.1 PSP-Net has been trained to detect people as a class. In our proposed system we will also use this approach by surrounding pedestrians labels with bounding boxes.

4.3 Fusion and Filtering

Once the semantic model and pedestrian detections are obtained the next step is to combine the information coming from different camera sources into a common plane. This is done in a process called fusion and filtering.

4.3.1 Multi-camera Scenario

Our system is developed in a multi-camera scenario. This is the essential setup to fusion information. This means that we are able to observe the scene from different point of views. In Figure 4.7 we can observe how the scene is configured with 3 static

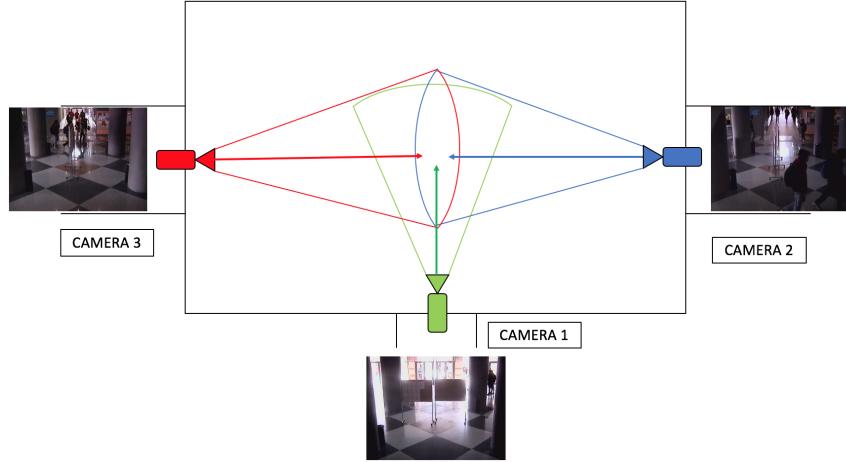


Figure 4.7: Multi-camera configuration

video-surveillance cameras. Two of them are placed at the sides of the scene, while one is at the bottom part. The starting views from the three static cameras are displayed in Figure 4.8.

As said in Chapter 2 working with a multi-camera scenario has some advantages. One can see in Figure 4.8 we can observe the same scene area from three different points of views, which means that for instance, detections from one camera can be used to detect in other camera or even refine the available detections.

4.3.1.1 Cenital Plane Homography

Homography calculation is a pivotal task in our work and the main base for the fusion of all the different information coming from the three cameras. The objective is to compute an homography matrix $\pi_{ref} H_F$ that relates one camera frame F_t at a time t , to a so called cenital plane π_{ref} , i.e. a bird-eye representation of the scene. With this homography matrix we will be able to transform every frame pixel $F_t(x_1, y_1)$ to its correspondent position in the cenital plane $\pi_{ref}(x_2, y_2)$. Frame perspective is so, transformed as if it were being viewed from the top. The homography process is also important as it enables to project pedestrians detections to the cenital plane with the same proceeding.

The formulation of the generic homography problem between two cameras and a plane is as follows:

We have two cameras C_1 and C_2 looking at the same exact points P_i in a plane. One wants to pass from the projection $p_i(C_2) = (u_i(C_2); v_i(C_2); 1)$ of P_i in C_2 to the projection P_i in C_1 defined as $p_i(C_1) = (u_i(C_1); v_i(C_1); 1)$.



Figure 4.8: Initial Camera Views

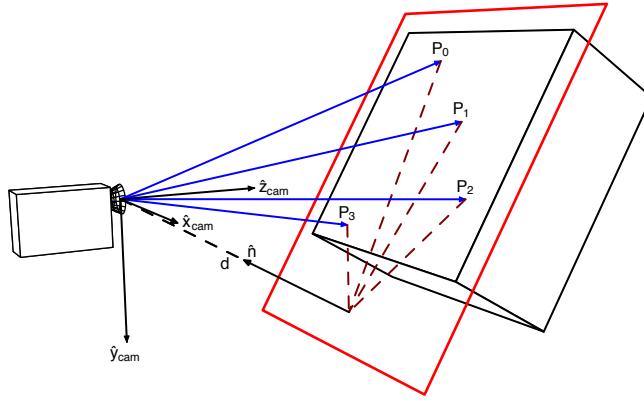


Figure 4.9: Generic homography problem. Camera and plane setup

To do this process Eq 4.1 should be computed.

$$p_i(C_1) = \frac{z_i(C_2)}{z_i(C_1)} K_{C_1} \cdot H_{C_2 C_1} \cdot K_{C_2}^{-1} \cdot p_i(C_2) \quad (4.1)$$

where $z_i(C_1)$ and $z_i(b)$ are the z coordinates of P in each camera frame and where homography matrix $H_{C_2 C_1}$ is defined as in Eq 4.2.

$$H_{C_2 C_1} = R - \frac{tn^T}{d} \quad (4.2)$$

where R is the rotation matrix by which C_2 is rotated in relation to C_1 . t is the translation vector from C_1 to C_2 . n and d are the normal vector and the distance to the plane respectively and finally K_a and K_b are the camera intrinsic parameters. Generic homography problem for one camera is depicted in Figure 4.9.

In order to compute an homography, a relation between at least 4 points in each of the two images should be computed. In this case a relationship between a real camera frame and a cenital view plane created by computer is needed. This means that there is not a real correspondence for pixels and so it is not possible to use a point descriptor to extract common points in both images. User has to manually select the points that represent the same spatial place in both images using the Graphical User Interface and then the algorithm computes the transformation matrix.

4.3.1.2 Cenital Plan Design

As said in the introduction of this Section, one of the main objectives of the work is to project the extracted detections from the three cameras, i.e. pedestrian and semantic, into a common plane for all of them. To achieve this goal a cenital plane that correctly represents the scene is needed. The first used approach for the cenital



Figure 4.10: First cenital plane approach

plane can be observe in Figure 4.10.

This cenital plane lacks of details from the scene. The information about the details of the scenario is minimum and also, the scene proportions are not correct. To compute a correct homography between the camera frame and the cenital plane we should be able to identify the same scene points in both images in the ground plane. This means that the cenital plane should have enough details so the point selection is done correctly by the user and the homography is correctly computed.

For this reason, and driven by bad results, another cenital plane has been computed starting from zero. In this new approach the scene has correctly been measured by hand and the plane has been done with real measures and high floor detail.

For correctly drawing the plane [AutoCAD 2017](#) software has been used. The second plane approach with all the manual measures extracted from the real scene superposed can be seen in Figure 4.11 while Figure 4.12 represents the final cenital map with the correct camera positions.

It is easily observable that differences between Figure 4.10 and 4.12 are outstanding both in floor details and in general construction proportions. This detail rise leads to a much more easy homography selection points by the user as it now has more point options to choose and evidentially this means that the final homography matrix, and so, all the projections are better accurately talking.

4.3.1.3 Camera Panning

When cameras are static and pointing to the center of the scene as in Figure 4.8 and 4.8 one can easily observe that the vision range compared to the hole scenario

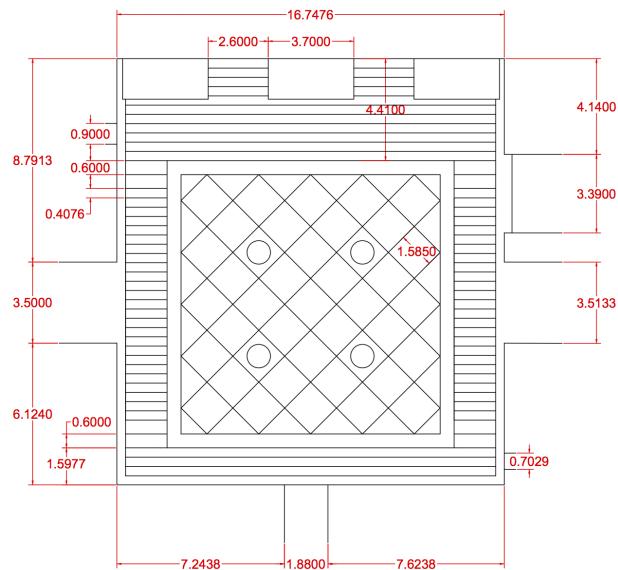


Figure 4.11: Second cenital plane approach with real measures

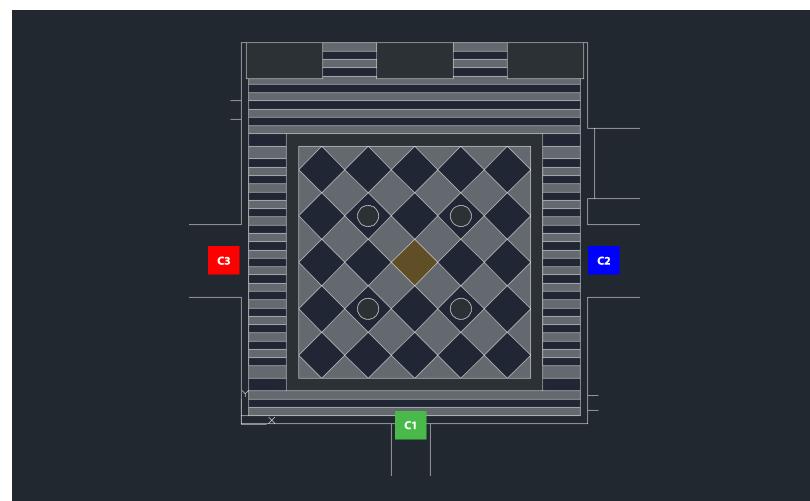


Figure 4.12: Second cenital plane approach with camera positions

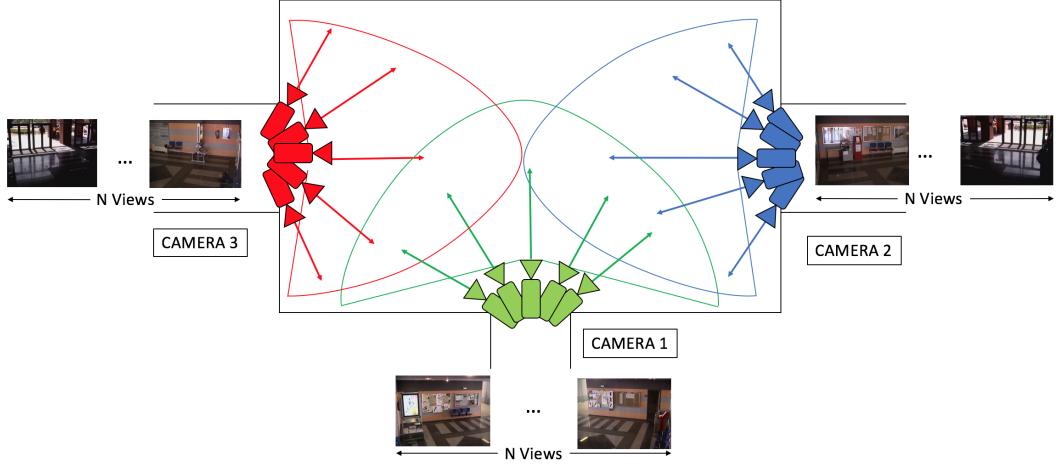


Figure 4.13: Multi-camera configuration with panning set up

representation is quite limited due to the low vision range of the cameras. The cameras are covering the middle part leaving completely unattended the lateral parts of the scenario. This approach is a limitation to the project objectives as high percentage of the scene semantic remains hidden.

The solution for this problem is to include panning movement thanks to the PTZ technology in all the cameras from left to right so cameras view range is increased and they are no longer focus only in the middle of the scene as before. This leads also to more common and not static areas which the cameras will share. This solution is presented in the scene diagram in Figure 4.13.

4.3.1.4 Camera Panning Discretization

Before including camera panning in the set up, homographies were calculated, at the beginning, for only one video frame per camera. This means that every camera only had one homography matrix as all its sequence was static and all its video frames were projected using the same matrix.

However, when including video panning this simple approach is no longer valid as the scene view is constantly changing. The ideal solution for this problem would be having one homography matrix $\pi_{ref} H_{Frame}$ per video frame. As the homographies are calculated by the user selecting the points this solution is evidently impossible in terms of usability.

We propose discretization of the panning tour in which N views are selected from the video sequence. This leads to the obtention of an homography codebook in where the user computes a homography matrix $\pi_{ref} H_{View}$ for each of the N camera views.

This codebook of views and homographies are responsible for projecting into the cenital plane the hole video.

4.3.1.5 View Selection

Due to the creation of the homography codebook we now have to choose between a set of N homography matrices to project detections into the cenital plane. The actual analyzed frame should be compared to each of the N views to obtain an spatial correspondence and so, use the correct homography matrix.

In order to compare two images we have done comparison between points of interest. AKAZE detector and descriptor [56] has been used for this task.

AKAZE is a fast multi scale feature detection and description approach. It exploits the benefits of nonlinear scale spaces. Previous approaches such as KAZE [57] or BFSIFT [58] have a main time consumption drawback in terms of nonlinear scale space creation. However, AKAZE uses recent numerical schemes called Fast Explicit Diffusion (FED) [59, 60] in order to speed up detections. In addition the use of the Modified-Local Difference Binary (M-LDB) descriptor increases the efficiency of the general approach.

AKAZE detects and describes points of interest in any image and then by a brute force comparator in terms of point distances we extract how many coincidence we have between a pair of images.

It is essential to say, that, as we have to compare the current frame with all of the N views there is a trade off. More views means a better space discretization and more overlapping between them, however, the computational time increases exponentially, this means that we have to choose the number of views N so it represents correctly the space and keeps the computational time relatively low. In our proposed system we have choose $N = 9$ to maintain a trade off between projection quality due to the overlap between the views and time consumption.

As we said before, the homographies are calculated for each of the views, this means, that if a frame is not positioned exactly as a view the homography matrix does not project the points correctly, there will be a small error. Taking advantage of the calculation of common descriptors between the frame and its correspondent view this problem can be solved by calculating automatically the homography between both images. This means that now, to project detections from the current frame to the cenital plane two homographies are used. First we change the perspective of the original frame to the perspective of the view with ${}^{View}H_{Frame}$. This process ensures that the used perspective is the same one as the one that was used previously to compute the homography. Finally, the frame and its new perspective are projected

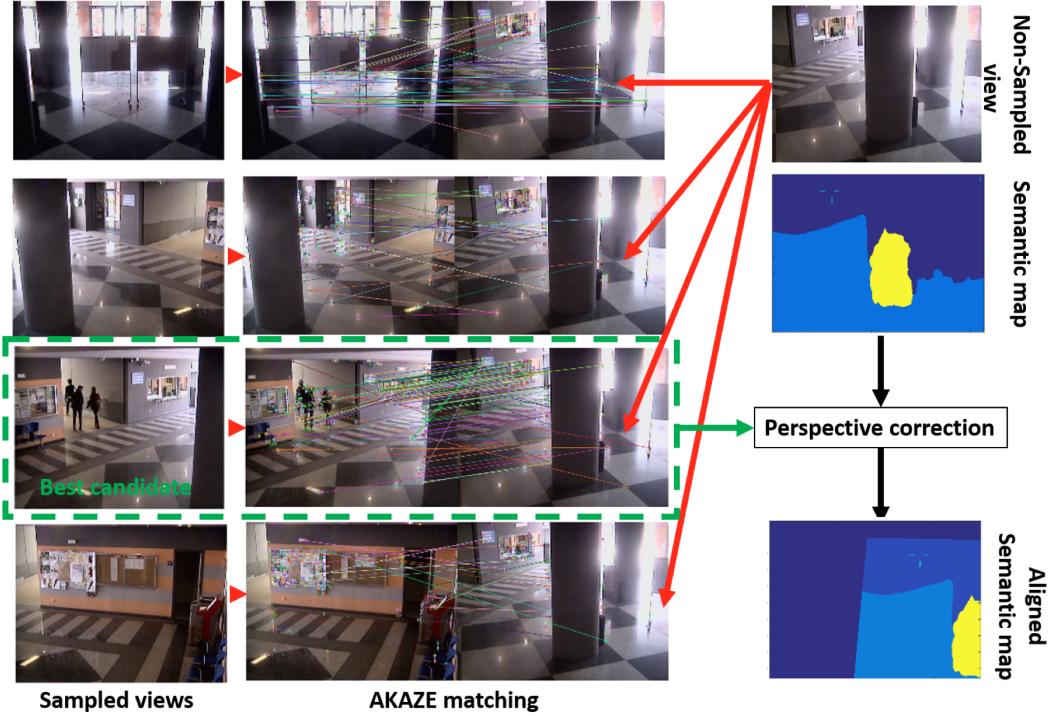


Figure 4.14: View selection process and homography between views computation.

to the cenital plane by means of $\pi_{ref} H_{View}$. This process is graphically explained in Figure 4.14.

4.3.1.6 Video Sequence Synchronization

One of the main issues when dealing with multi camera systems, and specially, those that combine information between the cameras, is that video sequences coming from them should be correctly synchronized. This is really important because if the same frame number F is not representing the same exact moment in time in the three cameras, combination and fusion of the information is not possible.

We have synchronized the processed videos using the so called clapperboard technique. This technique aims to synchronize using concrete events that can be observed from all the cameras at the same time. By this, we are able to set a synchronize starting point from where the following video frames are correctly representing the same moment in time.

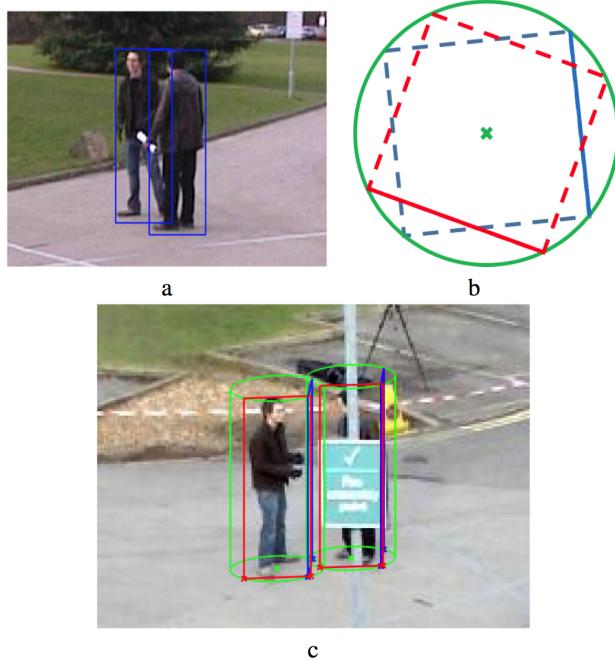


Figure 4.15: Cylinder estimation for camera instance projections. Extracted from [52].

4.3.2 Pedestrian Filtering and Constraining

During this Section we explain how the pedestrian detections are semantic filtered and also how the information between people from the three cameras is fusion in the system to increase the general algorithm performance.

4.3.2.1 Cylinder Estimation

In [52] a cylinder estimation technique is proposed. The detected bounding boxes on the camera frame do not correspond spatially with the exact position of the detected object due to the camera perspective. If this detection error is not corrected when the bounding boxes are projected either to another camera instance or to the common cenital plane there is a distance between the represented bounding box and the real object. Figure 4.15 shows the case for bounding box transference between cameras.

As we can observe in Figure 4.15 when the blue bounding boxes are projected from image (a) to image (c) they are not correctly on the pedestrian. The solution is to compute the cylinder that embraces the square whose side is the bounding box (b). Once the cylinder is estimated, the person will hypothetically be in the middle of the cylinder. In (c) we can observe that the estimation, if correctly computed has

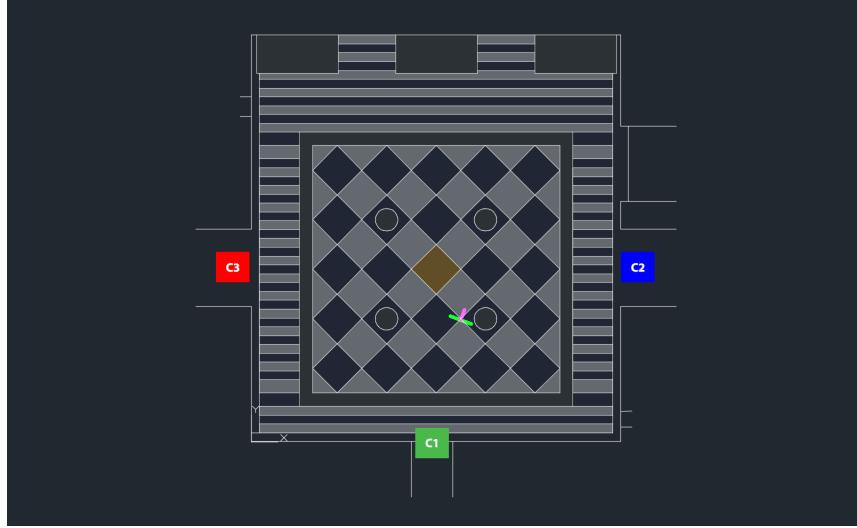


Figure 4.16: Cylinder estimation for cenital view projections.

great accuracy.

In Figure 4.16 the same method is applied but in this case, the bounding box is not projected to another camera perspective but to the cenital plane. The projection of the bounding box, represented by the green line is not in the same position as the center of the cylinder, which is at the end of the purple line. The center of the cylinder so, corresponds to a more approximate position of the detected person.

4.3.2.2 Gaussian Bounding Box Representation

Using also the cylinder representation one can change the way bounding boxes are represented in the cenital plane. As said before, in the simple cylinder representation pedestrian are represented with two perpendicular lines, however, in this representation one does have spatial information about the detection but none about the detection accuracy. This means that with the two perpendicular lines one can observed where the detection has been achieved but not the score associated with this detections. To solve this issue we propose a new representation method based on a Gaussian function placed at the middle of the cylinder.

Every pedestrian detection is so, represented as a Gaussian function of the form described in Eq. 4.3.

$$f(x, y) = A \exp \left(- \left(\frac{(x - x_0)^2}{2\sigma_x^2} + \frac{(y - y_0)^2}{2\sigma_y^2} \right) \right) \quad (4.3)$$

In this case A is the amplitude which typically is set to $A = 1$, x_0, y_0 represent the

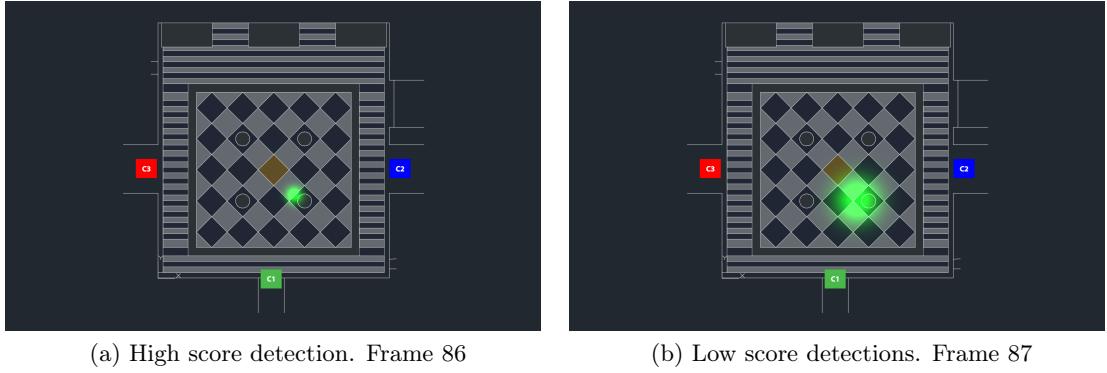


Figure 4.17: Gaussian representation examples.

mean of the gaussian which, in our case, is the center of the cylinder associated to the bounding box and σ_x, σ_y which is the standard deviation and in our case represents the accuracy of the detection.

In order to relate a detection score S_n with a determinate standard deviation a simple rule explained in Eq 4.4 is proposed.

$$\sigma_x = \sigma_y = (S_n \cdot 10) + 5 \quad (4.4)$$

This Equation has been adapted to the size of the used cenital plane. This means that detections with higher scores are represented as a narrow gaussian function (Figure 4.17a) while lower scores lead to wide gaussians that represent a bigger area in where one can find that person (Figure 4.17b). Some Gaussians examples depending on the scores can be observed in Figure 4.17.

4.3.2.3 Pedestrian Reprojection Between Cameras

When all the pedestrian detections have been projected into the cenital plane one can start reprojecting those projections from the cenital plane back to the other camera frames.

This process has a fundamental importance as it is from where the pedestrian detector accuracy can be increase by the use of the multi-camera system. For instance, detections from Cameras 2 and 3 are reprojected into Camera 1. Sometimes, those reprojections are not in the frame because the cameras are not aiming to the same spatial area, however, when they are seeing the same spatial space cameras share those detections. Ideally, if the three cameras detect the person reprojection could not be necessary, but, if one of them misses the detection, the other two detections, by the use of reprojection, lead to suppress that miss detection.

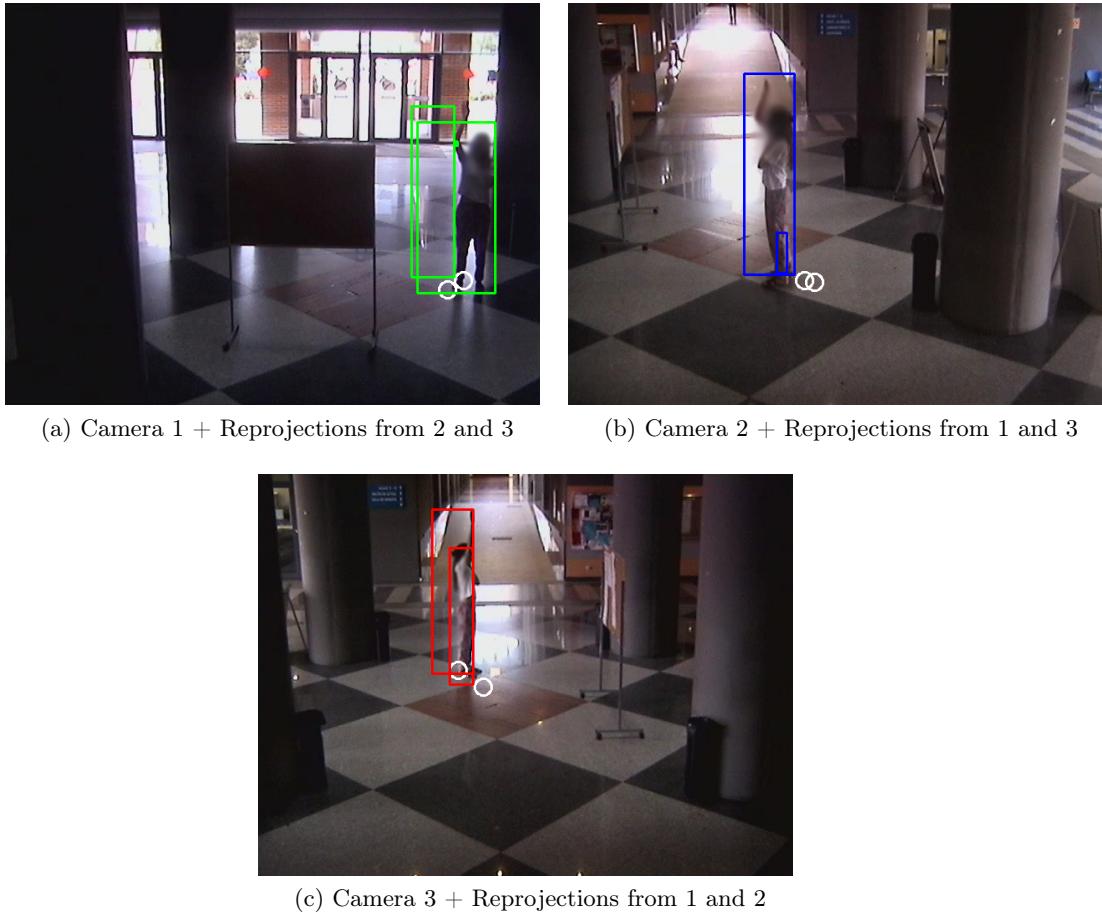


Figure 4.18: Pedestrian detection reprojection.

Projected frames from one camera to another are treated as another detector blob. This means that if the detection is accurate enough in the original camera, when projected to another frame it could be either joined by a Non-Maximum Suppression (NMS), if that camera has already one blob, or maintained as a detection on the person. However, if the detection is not accurate enough, the projection could be not on the person and so that blob leads to a false positive. This can be described as the main drawback of the method.

In addition, when blobs are projected from one frame to another blob height is lost due to the cenital projection. In order to achieve a complete blob once it has been reprojected, aspect ratio is used to, using the width of the blob obtain the height.

This process can be observed in Figure 4.18.



Figure 4.19: Pedestrian semantic constraining. Blobs that are not in the right semantic area are just displayed by a circle and text label.

4.3.2.4 Pedestrian Semantic Constraining

Once all the detections have been reprojected into all the cameras one can use semantic information in order to filter false positives detections in weird scene areas . Ideally people are always walking on the floor so the common floor areas between pairs of cameras, whose calculation is deeply explained Section 4.4.2, are used to constrain the pedestrian detections to this hypothesis. This process is done based on the cenital plane builded using the cylinder estimation explained before. The constrain idea is that a bounding box coming from a camera C_1 is assumed correctly computed if the center of its related cylinder is on the common floor between C_1 and C_2 and also between C_1 and C_3 . An example of the constraining can be observed in Figure 4.19.

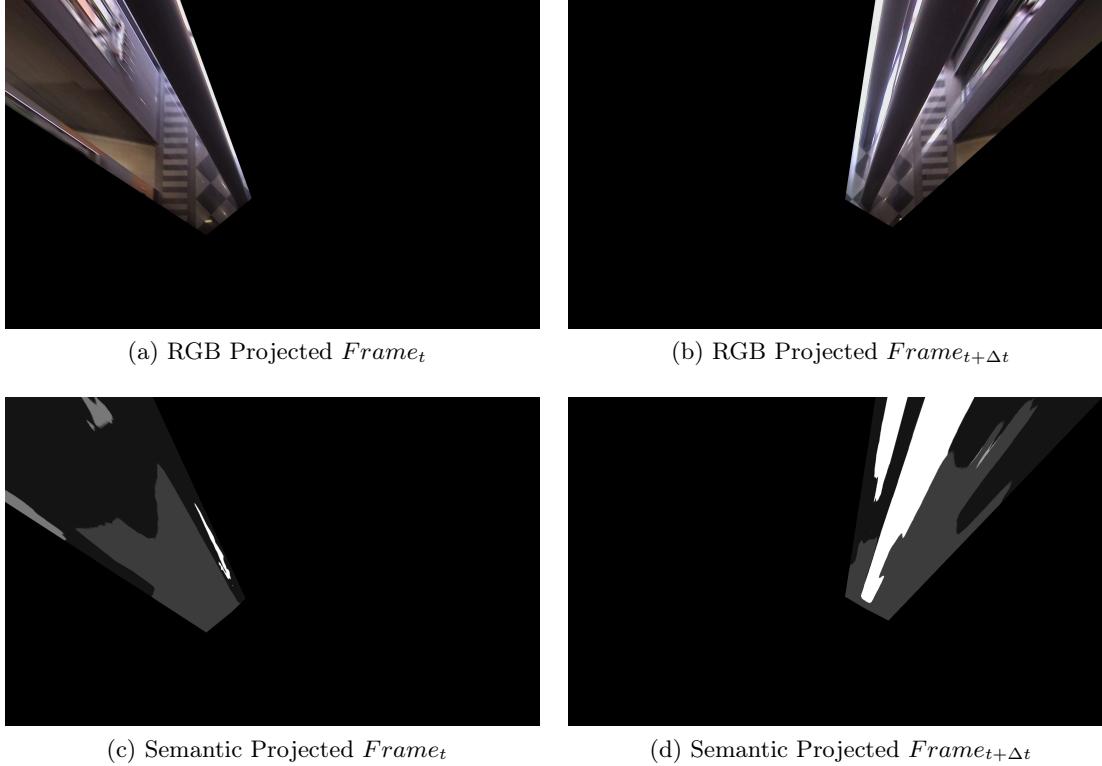


Figure 4.20: RGB and semantic frames projected.

4.4 Reference and Inertial Homography Planes

During this Section our proposed method to create both RGB and semantic reference planes combining information from all the cameras positions is explained. The final objective is to have complete maps in each camera that represent the scene.

4.4.1 Semantic and RGB Reference Plane Generation

Following with the process scheme of Figure 4.14 one can project every video frame into a cenital perspective. This way a set of projected RGB and semantic frames for each camera is obtained. Some examples of these images can be observed in Figure 4.20.

Once all the video frames are projected we propose to apply a temporal average through a median filter for the three cameras separately. By this method a reference plane π_{ref-C} for each camera contained in the ground plane is created by joining all the separated projected frames. This process is detailed in Eq 4.5(FORMULA MEDIAN FILTER? i ? i ? i).

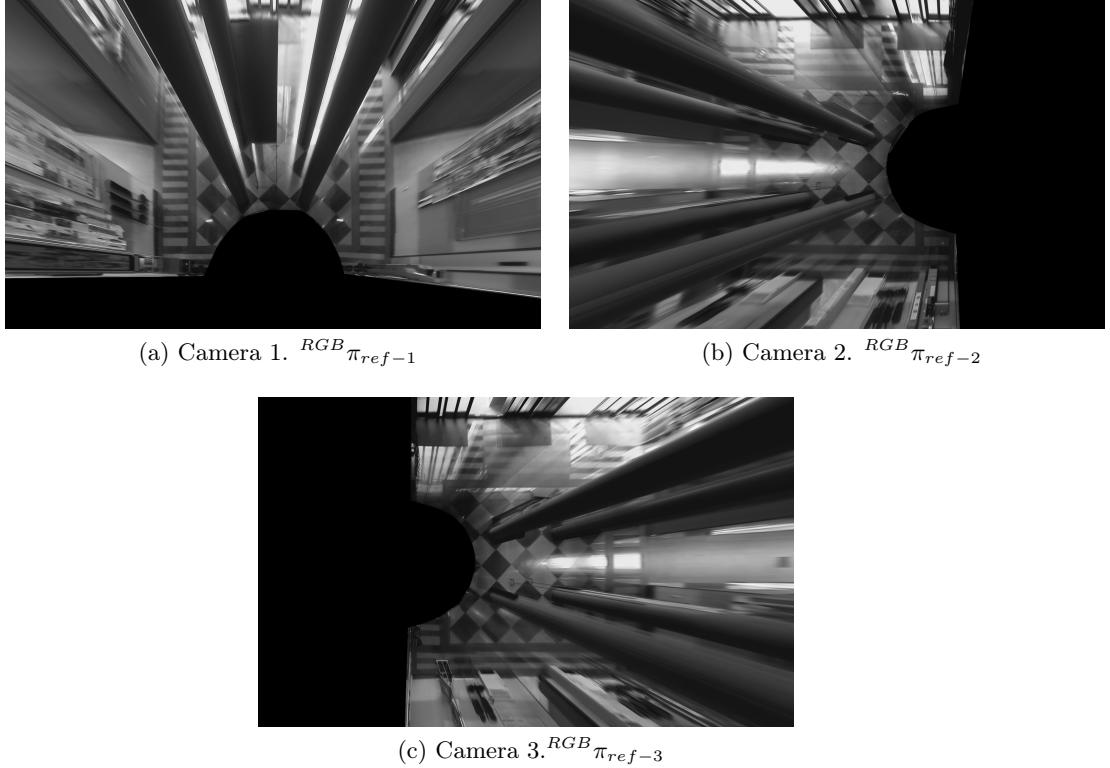


Figure 4.21: RGB Reference Planes ${}^{\text{RGB}}\pi_{\text{ref-C}}$.

$$\pi_{\text{ref-C}} = \sum_{i=1}^{n\text{Frames}} \text{Projected}_i \quad (4.5)$$

The result coming from the temporal averaging can be observed in Figure 4.21 for RGB case and in Figure 4.22 for semantic information.

As one can observe smooth semantic and RGB maps from all the hall area are created. It is important to recall that only if the homographies and the ground floor are correctly calculated and projected, the base of for instance the columns from all the different cameras, should lay in the same spatial point in these images.

4.4.2 Semantic Fusion in the Reference Plane

Once the cenital maps have been extracted one can combine them to create semantic fusion in the reference plane. The main objective is to obtain common areas, i.e. pixels with the same label within two or more cameras. This method allows us to increment the confidence for those pixels and so, we can use this information for example, to constrain pedestrians detections. As the reference plane is obtained by

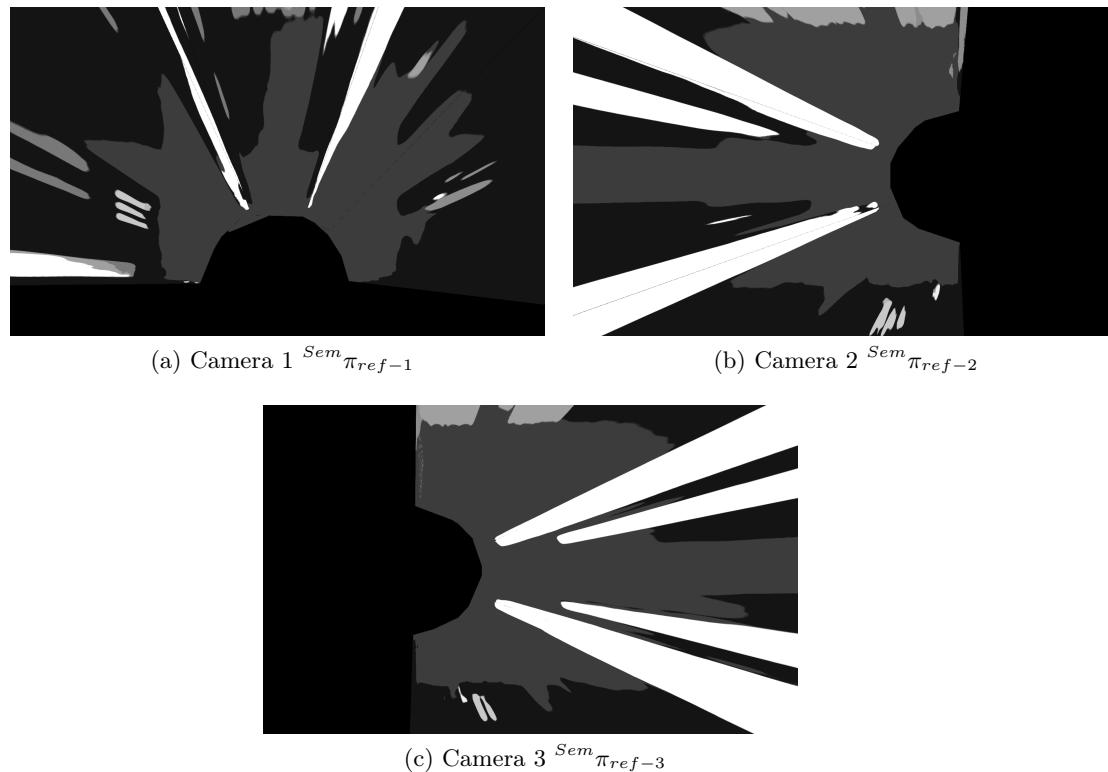


Figure 4.22: Semantic Median Average $S_{sem}^{\pi_{ref-C}}$.

the homography to the ground plane we have only take into account floor pixels to create the common areas, as the others have projection errors that lead to fusion errors.

First, pairs of cameras are combined to create three common semantic areas that are shown in Figure 4.23.

Once pairs of cameras have been combined one can go further and extract common areas for the three cameras at the same time. Those areas are pixels with the exact same label for the three cameras so its probability to be that class is really high. Figure 4.24 represents the common areas.

As we can observe, due to the multi camera setup and some scene occlusions such as scene panels or columns, the common area shared by all the cameras represents a small portion of the room. This is the reason why we have choose common areas between pairs of cameras to work along with pedestrian detection rather than common area between all of them.

4.4.3 Parametric Homographies Between Inertial Planes

Homography matrices, as explained before, aim to relate floor plane for a frame with the cenital view. However, everything that is not exactly in the same s plane is not projected properly when the homography matrix is used. In our work, different semantic are needed to be projected, for instance a door. When using floor homography only its base is correctly projected.

In [61] a solution to this problem is proposed. The general idea is to create a multilayer reconstruction. Once the homography matrix $\pi_{ref-C} H_{view}$ that relates the image view with the reference frame π_{ref-C} is calculated, one can obtain another matrix $\pi' H_{view}$ that relates the same image frame with a parallel plane called inertial plane at a fixed height Δt .

$\pi' H_{view}$ can be expressed as a function of $\pi_{ref-C} H_{view}$ and Δh as described in Eq 4.6.

$$\pi' H_v^{-1}(\Delta h) = \pi H_v^{-1} + \Delta h P \hat{\mathbf{k}}^T, \quad (4.6)$$

where $P = [u_0 \ v_0 \ 1]^T$ is the principal point of camera C and $\hat{\mathbf{k}}$ is the unit vector of the Z axis.

All this process is described in Figure 4.25.

By this process, ideally a number k of planes could be generate (Figure 4.26) in which different object sections are correctly projected. It could lead to a complete semantic map in which all the pixels represent semantic areas that have been correctly

(a) Cameras 1 and 2. ${}^{Sem}\pi_{ref-1} \wedge {}^{Sem}\pi_{ref-2}$ (b) Cameras 2 and 3. ${}^{Sem}\pi_{ref-2} \wedge {}^{Sem}\pi_{ref-3}$ (c) Cameras 3 and 1. ${}^{Sem}\pi_{ref-3} \wedge {}^{Sem}\pi_{ref-1}$

Figure 4.23: Common semantic areas between pair of cameras.



Figure 4.24: Common semantic areas for all the cameras $Sem\pi_{ref-1} \wedge Sem\pi_{ref-2} \wedge Sem\pi_{ref-3}$

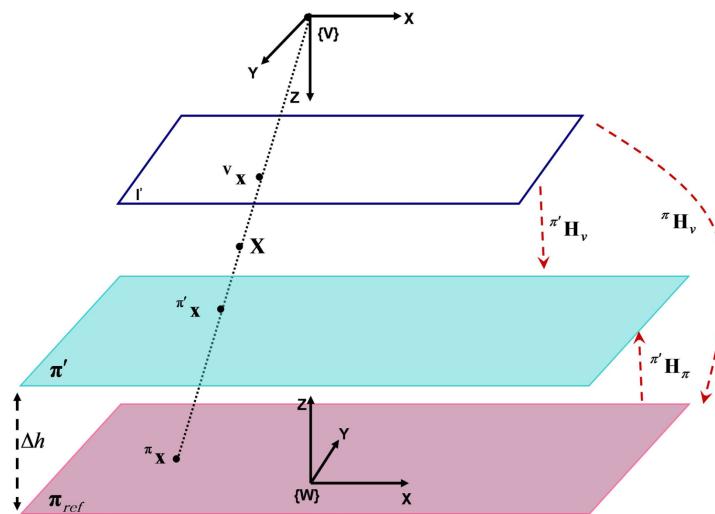


Figure 4.25: Extending homography for planes parallel to π_{ref} . $\pi_{ref} H_V$ is the available homography between camera view and reference plane π_{ref} either semantic or RGB.

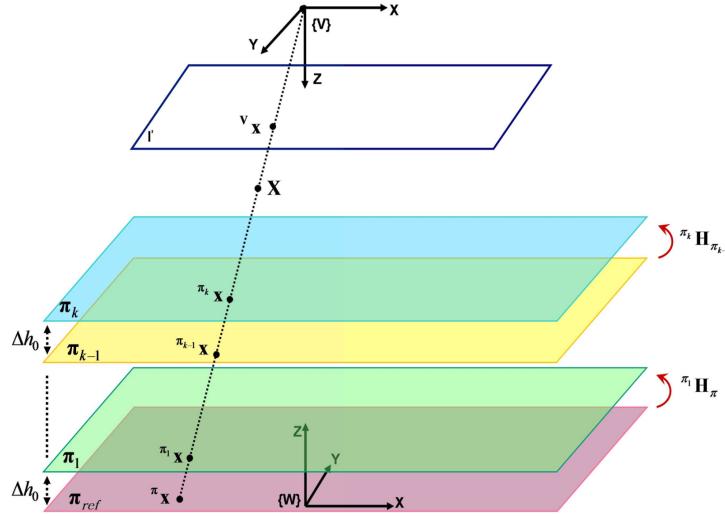


Figure 4.26: Set of k inertial planes π_k . Each inertial plane is separated from the other by the same Δh height

projected.

4.5 Statistical Usage Data

Along this Section we explain the proposed system to extract statistical usage data frame by frame given a sequence. The aim is to obtain one graph per selected class that measures the amount of people at a moment t of time in the determined semantic area during the sequence.

In order to extract usage data the first step is to create a projected common semantic map. For this task, rather than creating common areas between cameras as done for the PD constraining, information for all the cameras have been joined without strictly being shared. This have been done to preserve as much semantic as possible and so, have bigger floor or door areas than if we were more restrictive.

The result from this step is a unique map that represents the hole spatial area (Figure 4.27).

As one can observe we have decided to only take into account for this process floor, doors and chairs, which are the most accurate detections from the semantic segmentation. Following the same principle as in the previous Section, pedestrians are projected on to the statistical semantic map and so one can be able to know how many people are in each of the designed areas.

In addition, one can divide Figure 4.12 into different subregions of fixed size and extract in which of them pedestrians are more likely to be. This process leads to a



Figure 4.27: Statistical semantic map.

set of most used paths.

Chapter 5

Results

During this Chapter all the achieve results are exposed and analyzed. Firstly, a brief analysis of the used hardware during the Thesis is done. Secondly, in detail, the experiment setup is explained, i.e. the generated data-set and ground truth, and the evaluation framework. Later, results concerning application performance are presented. Homography projections results are analyzed. Finally, the last two sections aim is to present pedestrian detection results in term of performance and usage data extraction.

5.1 Used Hardware

The project has been developed in the Escuela Politécnica Superior (Universidad Autónoma de Madrid). Due to this fact, the testing environment has been the hall of the mentioned engineering school which has a setup of three different Internet Protocol Cameras (IP Cameras). This type of cameras can send and receive data via a computer network and Internet which allows the user to set the configuration and receive frames from the cameras.

5.1.1 Camera Specifications

Specifically, the camera model used along the project has been the Sony SNC-RZ50P PTZ Camera . This is a PTZ camera which means that it will be able to Pan, Tilt and Zoom all over the scene. Precisely this camera has a pan range of 340 degrees and a tilt range of 115 degrees, enabling users to monitor a wide area over the scene if the camera is moved (Figure 5.1) .

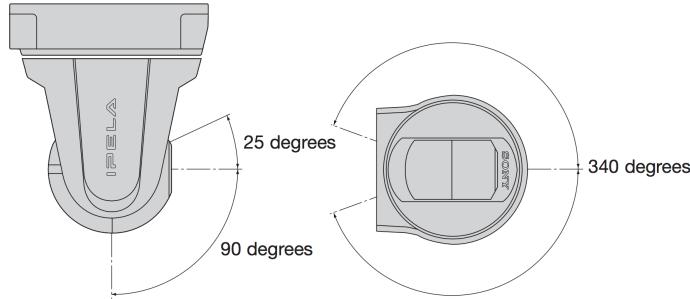


Figure 5.1: Sony SNC-RZ50P Pan/Tilt Range diagram

The complete and relevant specifications from the cameras are detailed in Table 5.1. In the scope of our work the most important features are resolution and frames per second that enable us to have more quality in both image and video.

Camera	
Horizontal viewing angle	1.7 to 42.0 degrees
Focal length	$f = 3.5$ to 91.0 mm
F-number	F1.6 (wide), F3.8 (tele)
Minimum object distance	320 mm (wide), 1,500 mm (tele)
Pan angle	-170 to +170 degrees
Pan speed	300 degrees/s (max.)
Tilt angle	-90 to +25 degrees
Tilt speed	300 degrees/s (max.)

Image	
Image size (H x V)	640 x 480, 320 x 240, 160 x 120
Compression format	JPEG, MPEG-4, H.264
Maximum frame rate	JPEG/MPEG-4 25 fps (640 x 480) H.264 8 fps (640 x 480)

Table 5.1: Sony SNC-RZ50P Specifications

5.1.2 Camera User Web Interface (GUI)

The camera comes with a built-in web interface that helps the user to visualize the visual range and set the different parameters that would change the camera behavior. The most important features that users are able to tune are described as follow:

- Camera control: Through this interface one can control and set the position of the camera in terms of pan, tilt and zoom (Figure 5.2). Changes in this three variables lead to different visualizations of the scene.

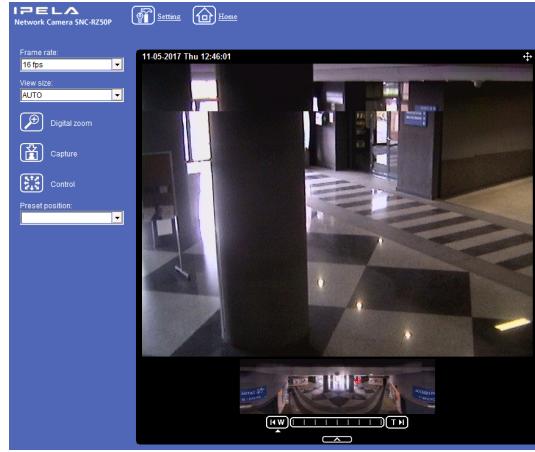


Figure 5.2: Visualization and control menu

- Preset position: In this menu (Figure 5.3) one could save the position that has been set in Figure 5.2 in order to recover the same position if the camera has been moved before in precise and easily manner.



Figure 5.3: Preset position setting menu

- Tour setting: One could apart from pointing the camera to a static point, set it to describe a tour over the scene. This process is done by setting at least

two different preset positions from where the camera is moving from one to the other at a set speed. The menu to configure this behavior is displayed in Figure 5.4.

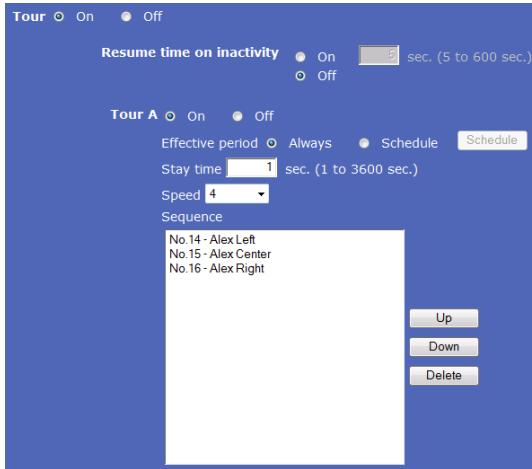


Figure 5.4: Tour setting menu

5.2 Experiment Setup

For all the experiments that are going to be analyzed along this Chapter the experiment setup should be explained. In this section, the generated data-set and ground truth and the proposed evaluation frame work used to obtain results are detailed.

5.2.1 Data-set

As said at the beginning of the Chapter the data-set has been generated in the university hall. The number of available PTZ cameras in the university is three so we have been able to record different sequences from three points of view. In addition, as explained in the previous Chapter a tour for each camera has been set so they move from left to right only changing position in the X/horizontal axis and not in the Y/vertical direction because of the reasons presented in Chapter 4.

Both settings are configured as previously displayed in the diagram of Figure 4.13.

The complete data-set consists on a set of three different recordings about 5 minute long from three different days. In each of the recordings all the camera sequences are available. Figure 5.5 shows some example of them. The technical characteristics of the videos are the detailed in the following lines:

- Number of videos per recording: 3



Figure 5.5: Data-set example frames

- Resolution: 640x480 pixels.
- Frame rate: 23.976 fps.
- Format: MPEG Video.

5.2.2 Ground Truth Generation

We have selected one of the three recordings from the data-set to completely evaluate the system. In order to do the evaluation ground truth information is needed. The video has been manually annotated with [Via Annotation Tool](#) to generate real pedestrian bounding boxes. This software allows the user to generate XML files with position and type of bounding box through the hole sequences. The recording consists on three different videos of 8300 frames, which means that the total number of manually annotated frames has been 25.200.

In Figure 5.7 annotated frames for the recording in different video situations can be observed.

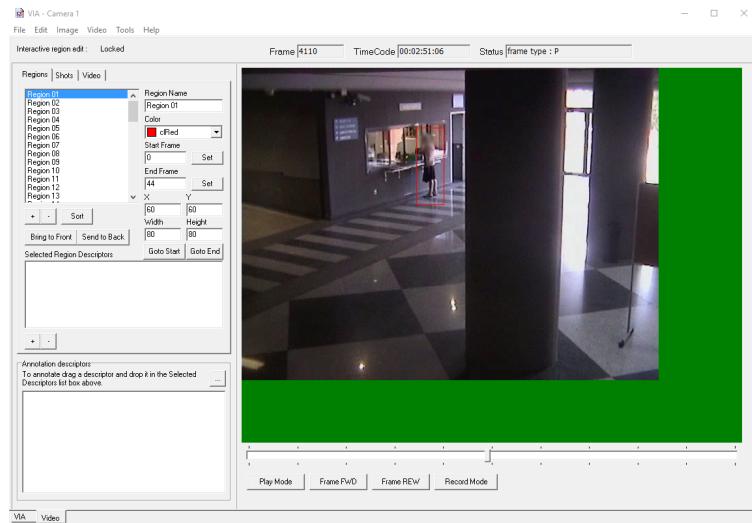


Figure 5.6: Via Annotation Tool software main window

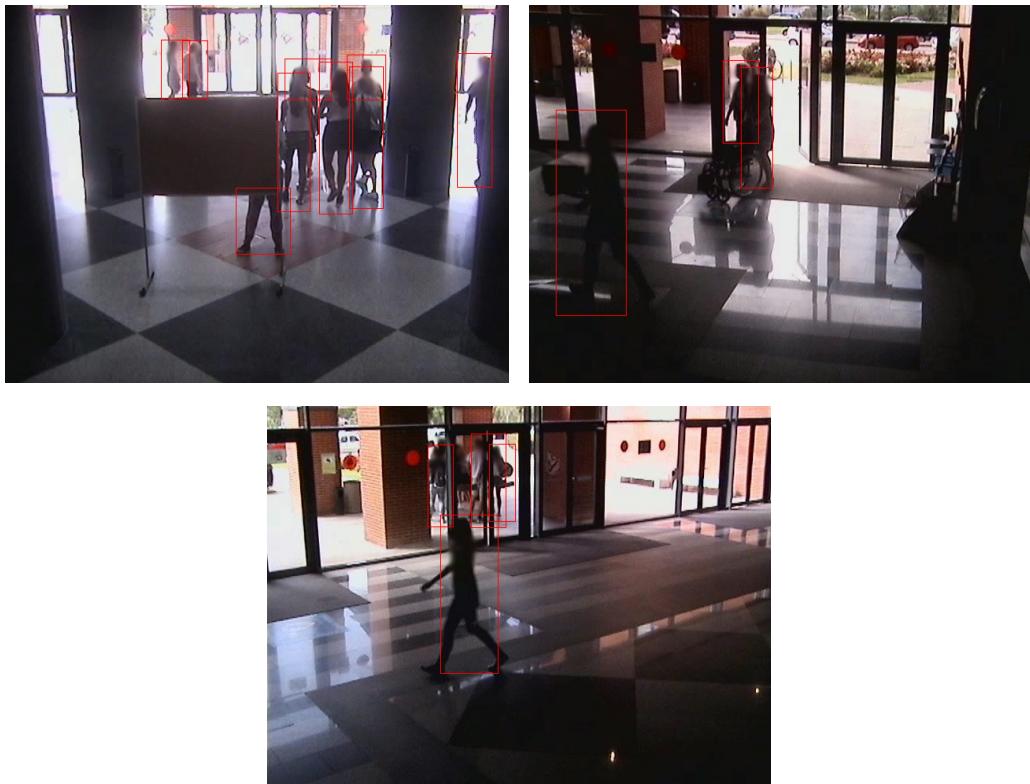


Figure 5.7: Annotated ground truth frames

As one can observe in Figure 5.7. The selected sequence for evaluation purposes is a mix between easy and difficult situations for a pedestrian detector. Situations go from people walking alone across the hall, to people pushing objects like a wheelchair, in addition to big groups of people both inside and outside the building or others where people are always occluded. In general due to image quality in terms of resolution and illumination and pedestrian situations the selected sequences are in the medium-high range of difficulty for pedestrian detection.

5.2.3 Evaluation Framework

Once the data-set recording has been correctly annotated one can proceed to evaluate the performance of pedestrian detectors. In order to evaluate these algorithms precision and recall metrics are used. The calculation of these metrics is defined in Eq. 5.1 and Eq. 5.2, respectively.

$$\text{Precision} = \frac{\#\text{True Positives}}{\#\text{True Positives} + \#\text{False Positives}} \quad (5.1)$$

$$\text{Recall} = \frac{\#\text{True Positives}}{\#\text{True Positives} + \#\text{False Negatives}} \quad (5.2)$$

Precision gives us information about the classification stage, whereas recall provides overall system performance information.

In addition, to measure performance in a more general process F-Score is used. It combines both Precision and Recall in a unique metric measure. Eq 5.3 express the general formula.

$$F - \text{Score} = \frac{(2 \cdot \text{Precision} \cdot \text{Recall})}{(\text{Precision} + \text{Recall})} \quad (5.3)$$

To extract the mentioned metrics we should have a method to compute which bounding boxes match with the ground truth. In order to achieve this objective Intersection over Union (IoU) or Jaccard metric has been selected. IoU is computed as in Eq 5.4 and it measures the relation between bounding boxes overlapping and its union areas.

This means that even if the bounding boxes overlap perfectly, but the union area of them is high, IoU metric will have a small value. This effect can be observed in Figure 5.8 where one can see that a almost perfect overlapping between bounding boxes does not lead to a high IoU value. For our evaluation framework a detection is consider correct if $\text{IoU}(\text{Detection}, \text{Ground Truth}) \leq 0.5$ which is the usually metric value selected in the State of the Art.

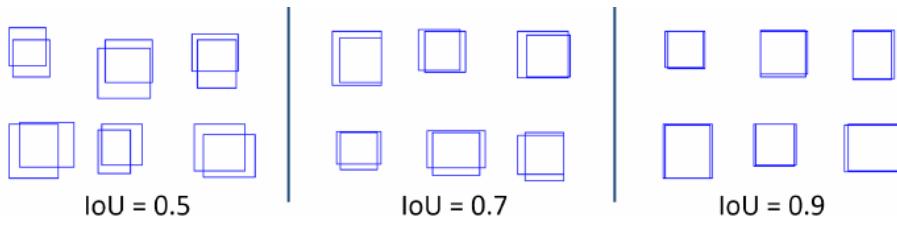


Figure 5.8: Intersection over Union or Jaccard Index

	Seconds/Frame	FPS
Single-Thread		
Multi-Thread		

Table 5.2: Comparison between the use of single thread or multi threads

$$IoU(Detection, Ground\ Truth) = \frac{OverlapArea(Detection, Ground\ Truth)}{UnionArea(Detection, Ground\ Truth)} \quad (5.4)$$

5.3 Application Performance

Along this section evaluation for the application in terms of general computational time is done.

Firstly, results concerning single thread and multi thread application are exposed. All the computations to extract and visualize pedestrian detections are measured. In Table 5.2 one can observe the difference in term of seconds per frame and frame per second for the same video sequence and the same pedestrian detector approach.

In addition, all the PD are compared when evaluated in the multi thread environment with the same video sequence. This results can be seen in Table 5.3

	Seconds/Frame	FPS
HOG		
ACF		
DPM		
PSP-Net (Offline)		

Table 5.3: Comparison between the use of single thread or multi threads

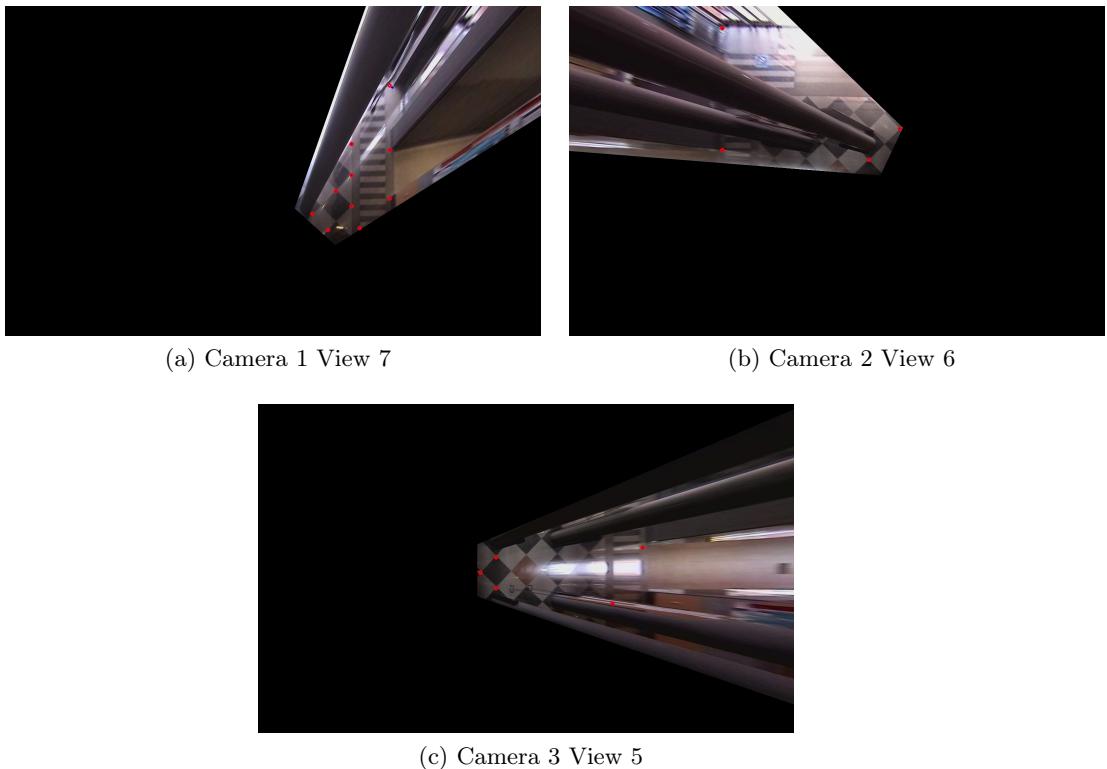


Figure 5.9: Projected views with homography matrices and overlapping of selected points.

5.3.1 Application Performance Results Discussion

Looking at Table 5.2 one can easily derive that the speed up of using multithread is clear.

5.4 Homography Calculation

First results concerning with the proposed system deal with homographies. As said in the previous Chapter correctly calculated homographies are essential for the right performance of further algorithms. In order to test that homographies have been correctly done by the manual selection of points views have been projected with its correspondent matrix. In addition, selected points from both the frame (blue points) and the cenital plane (red points) have been overlapped. Some examples can be observed in Figure 5.9.

5.4.1 Homography Results Discussion

As one can observe in the mentioned Figure, homographies are correctly calculated in most of the cases. Blue points are not visible because of the overlapping with the red ones, which means that their correspondence is perfect. However, some small errors can be noticed in Figure 5.9a where there exists a displacement between some red points and the blue ones (top of the image).

It is important to notice in this results how precision and image quality is reduced the further the points are from the camera. This is a standard problem when dealing with such type of homographies.

5.5 Semantic Segmentation

In this Section some results concerning the performance of PSP-Net in the proposed environment are presented. In order to test the algorithm and for the lack of semantic ground truth results should be visually evaluated. For this purpose Figure 5.10 is used.

5.5.1 Semantic Segmentation Results Discussion

Taking a look to results one can derive that PSP-Net extracts high quality results in terms of semantic. It is noticeable that most of the floor, if it is not occluded as in the top image from Figure 5.10, is correctly extracted. Pedestrians are also detected although performance in pedestrian detection scope is analyzed in the following section.

However, it is important to point that segmentation is not perfect when dealing with difficult illuminations or complicated objects. It can be observed that columns are not really correctly segmented. There are even some that are mistaken as walls which is a problem for our system. In addition, crystal doors such as the ones displayed in the top and bottom images are not correctly distinguish from building and wall labels which is a main issue for further algorithms.

5.6 Pedestrian Detection

During this section results in the context of pedestrian detection are presented. We propose a set of four different experiments to test our developed system.

The first one, tests all of the previously analyzed pedestrian detections working in a mono-camera environment. This means that neither information is shared by the cameras nor semantic constrains are applied.



Figure 5.10: RGB frames and PSP-Net Semantic segmentation results. From top to bottom: Camera 1, Camera 2, Camera 3.

Pedestrian Detector	Mono Camera	Multi Camera	Mono Camera Semantic	Multi Camera Semantic
HOG				
DPM				
PSP-Net				

Table 5.4: F-Score comparison between all the experiments and pedestrian detector approaches.

We will follow testing the algorithms in a multi-camera setup. As explained in 4.3.2.3 detections from cameras will be projected into the others to try to achieve better results than in a mono-camera scenario.

Thirdly, we will analyze people detection again in a mono camera environment but this time, applying semantic constraining as proposed in Section 4.3.2.4 for all the detections.

Finally, the last test will embrace all the proposed algorithms working within the multi-camera setup and applying semantic constraints.

It is important to remind that results are presented within Recall versus Precision curves. In order to create these graphs algorithms have been evaluated in all the four test using five different values for the score thresholding $[0, 1]$ interval. Each threshold iteration $(0, 0.2, 0.4, 0.6, 0.8)$ for an algorithm provides one point of the curve. To proceed with this process all the algorithms scores have been normalized from its original values using the maximum and minimum scores to the mentioned interval. In order to obtain scores distributions for all the detectors a train sequence has been used.

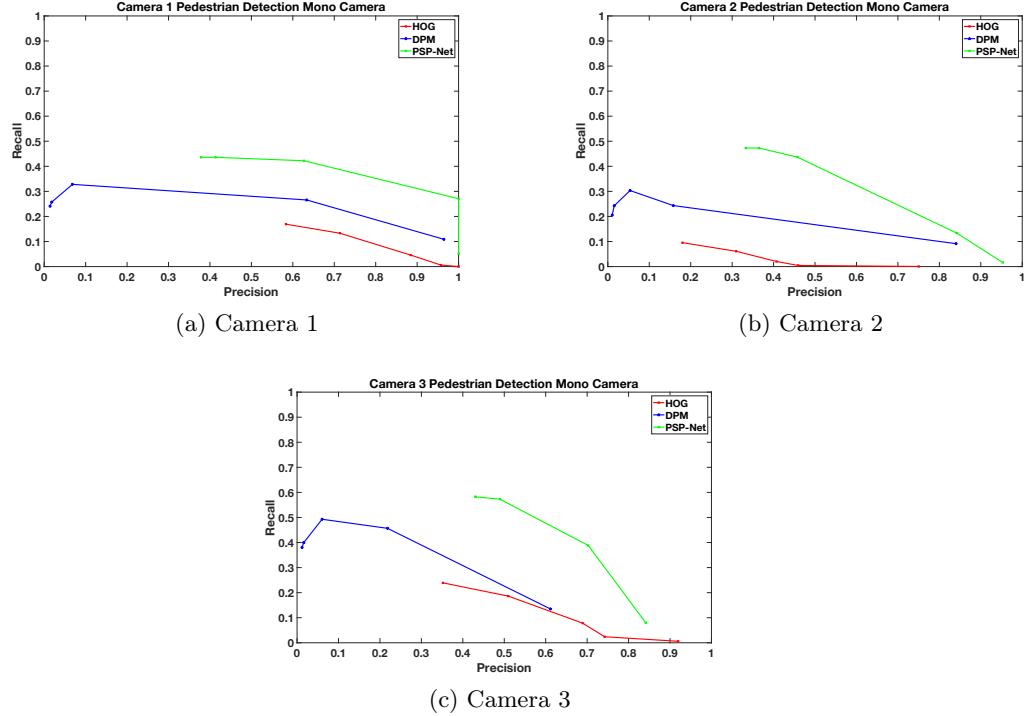


Figure 5.11: Recall / Precision graphs for mono camera pedestrian detection.

5.6.1 Mono-Camera

5.6.2 Multi-Camera

5.6.3 Mono-Camera with Semantic Constraining

5.6.4 Multi-Camera with Semantic Constraining

5.6.5 Pedestrian Detection Results Discussion

5.7 Statistical Usage Data

Finally, results concerning statistical usage data are presented. As said in the previous Chapter, we obtain one graphic per selected semantic area, which in our case are floor and door due to the usage of the mentioned map in Figure 4.27. The obtained curves are displayed both in Figure 5.15.

In addition, some results about the most used areas of the hall have been extracted. The hole area has been divided into regular subareas of fixed size in which pedestrian flow has been measured. By using this method one could have information about the most used paths by people over the scene. Results concerning this process are

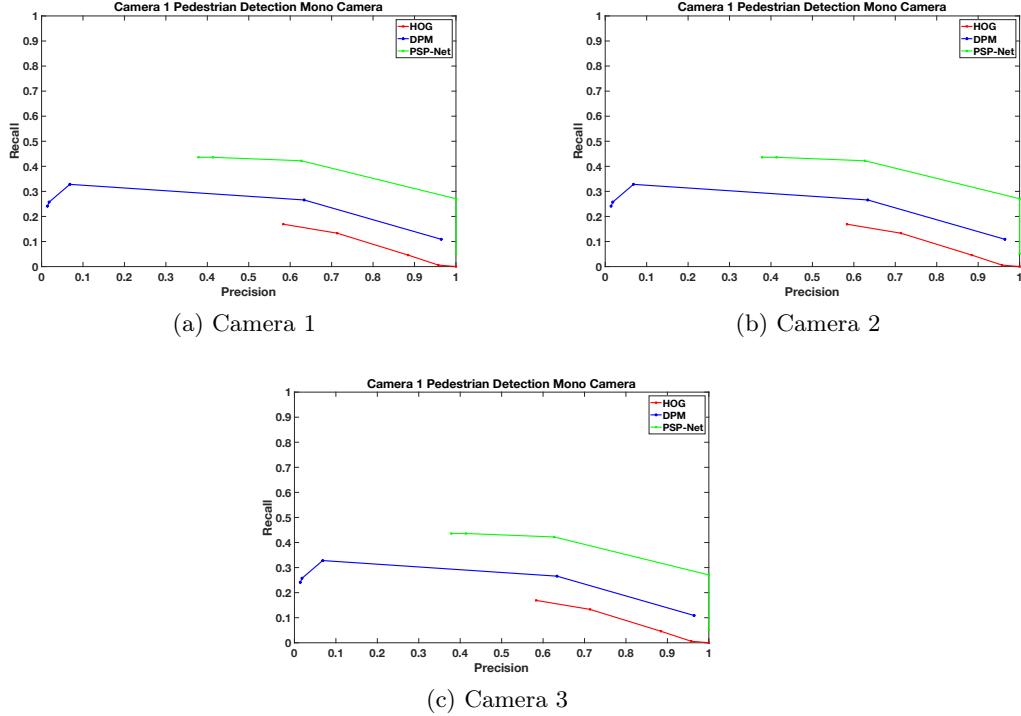


Figure 5.12: Recall / Precision graphs for multi camera pedestrian detection.

displayed in Figure 5.16 for a subregion size of 40×40 pixels and in Figure 5.17 for a subregion size of 70×70 pixels. A temporal comparison have been made with the correspondent frame.

Results are displayed as yellow squares that measure the amount of pedestrians found in that sub region. The more strong the color means that pedestrian density over that area has been higher than in the neighborhood.

5.7.1 Statistical Usage Data Results Discussion

One can observe in Figure 5.15 that both semantic areas are measured in terms of number of people by frame. If one takes a look to the correspondent frame, displayed at the top of the graph, it can be observed that there is a correspondence between the period when most people are walking through the scene and the peak from the curve. Same observation can be made when talking about doors usage as people passing through doors are in frame 5000 .

In both Figures 5.16 and 5.17 one can observe that most used paths increase accordingly to developed events in the sequence. For that reason when a person enters the building areas surrounding the door get highlighted. In the same manner, when

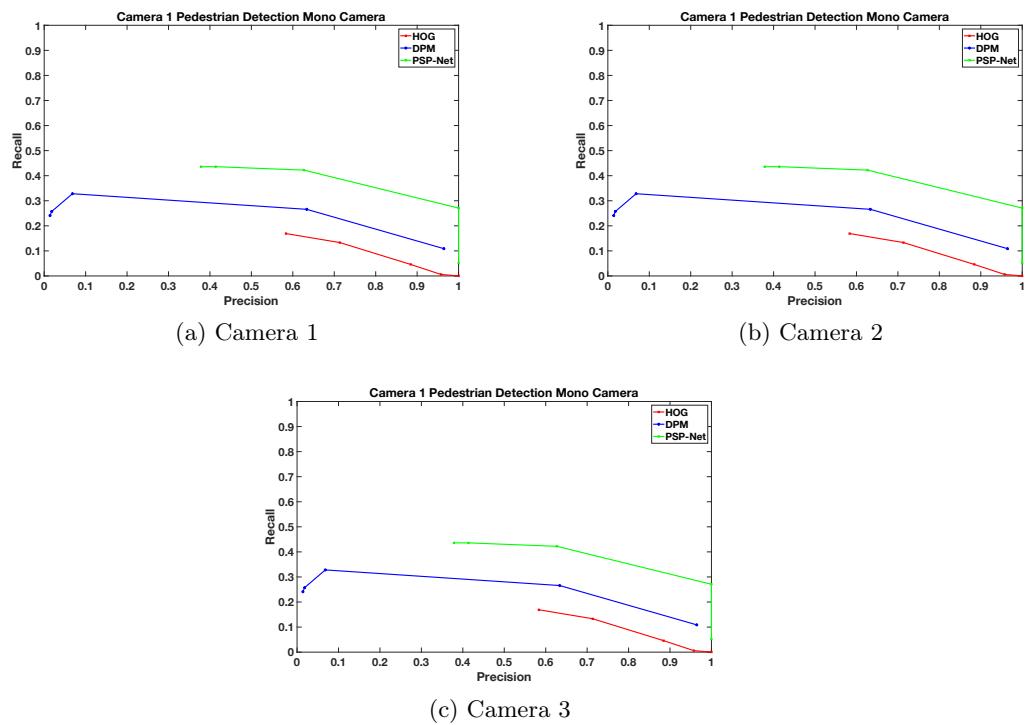


Figure 5.13: Recall / Precision graphs for mono camera pedestrian detection with semantic constraining.

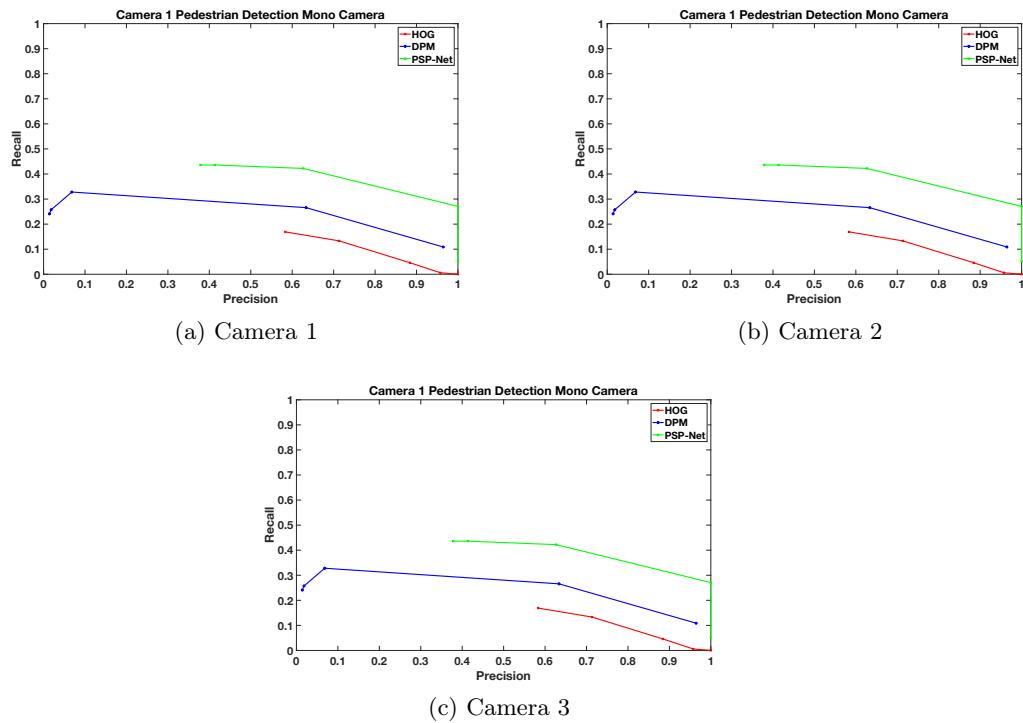


Figure 5.14: Recall / Precision graphs for multi camera pedestrian detection with semantic constraining.

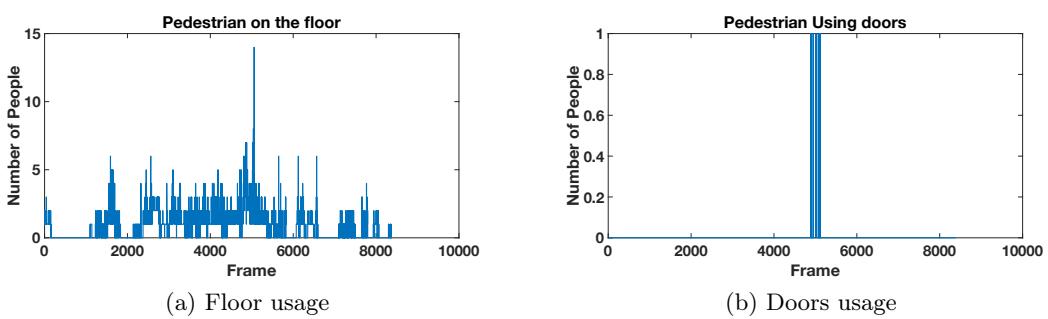


Figure 5.15: Statistical data usage curves in terms of pedestrian number/frames

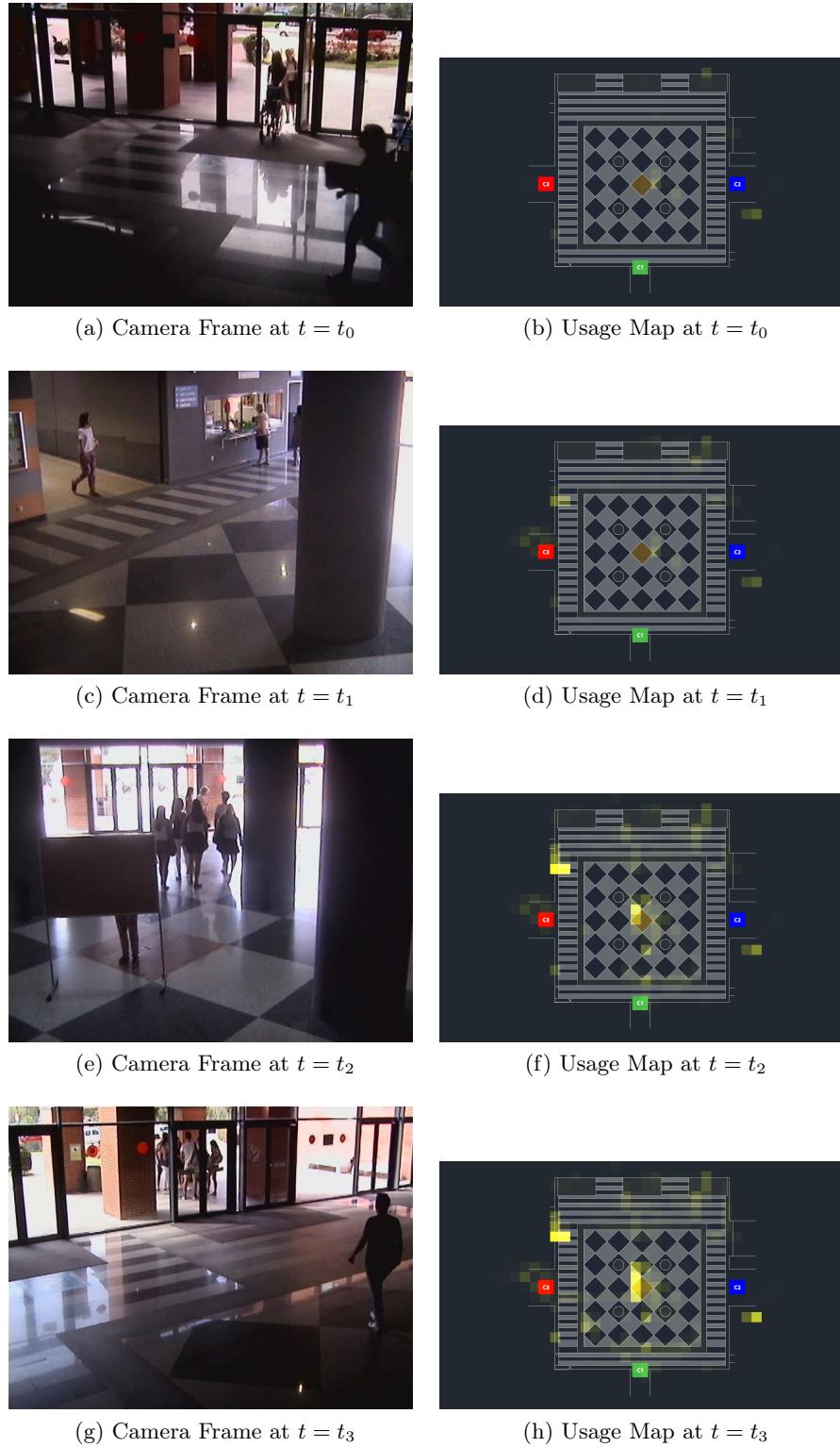


Figure 5.16: Pedestrians paths usage along the Hall. Scene has been divided in sub regions of 40 pixels.

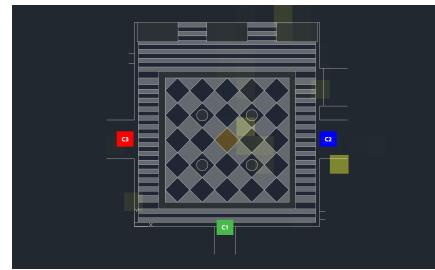
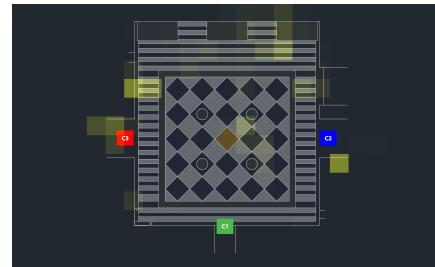
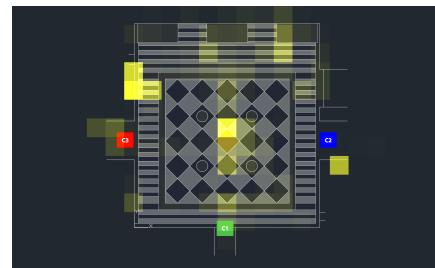
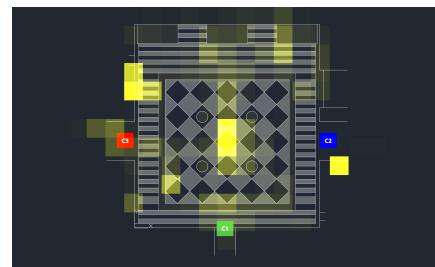
(a) Camera Frame at $t = t_0$ (b) Usage Map at $t = t_0$ (c) Camera Frame at $t = t_1$ (d) Usage Map at $t = t_1$ (e) Camera Frame at $t = t_2$ (f) Usage Map at $t = t_2$ (g) Camera Frame at $t = t_3$ (h) Usage Map at $t = t_3$

Figure 5.17: Pedestrians paths usage along the Hall. Scene has been divided in sub regions of 70 pixels.

a big pedestrian group walks along the scene all their trajectory is being highlighted as pedestrian density over that areas is highly increased.

5.8 Overall Discussion

Chapter 6

Conclusions and Future Work

6.1 Conclusions

Cuando hay cambios de iluminacion bruscos la seleccion de vistas falla.

Debido a fallos del detector las proyecciones no se corresponden exactamente con la persona.

Debido a las perspectivas, las reproyecciones de personas en otros frames tienen un ancho minimo y al aplicar la formula para la altura, est^a, sale muy pequena.

6.2 Future Work

Taking into account actual state of the art, obtained results and extracted conclusions one can set the stage for future work.

In term of application and software development some improvements are proposed to be done. Nowadays, heavy computational work is achieve almost in real time by the use of graphic cards. GPU computation should be implemented in the scope of this work. Many of the used method are also developed with GPU functionalities and the inclusion of this kind of speed-up could lead to better and faster results.

In other term, the proposed system bases all its performance in the correct view selection as explained in Section 4.3.1.5. However, as said in Conclusions when high illumination changes occur this process fails. We propose to fix this problem by the use of camera spatial positions. With this information exact same position for each of the views can be obtained and so, they can be updated during the video sequence in order to adapt to illumination changes.

One of the main problems discussed in the conclusions section is that when pedestrians are reprojected the blob height is lost. Due to this, there are some frames that

have small detections compared to the person size. To correctly reproject the blob we propose as future work to use real distances between camera and bounding box to finally obtain the real height for the blob.

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