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Deliverable D3.1

Proof-of-concept on data acquisition platform for risk evaluation and AID systems

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Consortium - List of partners

Partner No	Short name	Name	Country
1	UIC	International Union of Railways	France
2	VTT	Teknologian tutkimuskeskus VTT Oy	Finland
3	NTNU	Norwegian University of Science and Technology	Norway
4	IFSTTAR	French institute of science and technology for transport, development and networks	France
5	FFE	Fundación Ferrocarriles Españoles	Spain
6	CERTH-HIT	Centre for Research and Technology Hellas - Hellenic Institute of Transport	Greece
7	TRAINOSE	Trainose Transport – Passenger and Freight Transportation Services SA	Greece
8	INTADER	Intermodal Transportation and Logistics Research Association	Turkey
9	CEREMA	Centre for Studies and Expertise on Risks, Environment, Mobility, and Urban and Country planning	France
10	GLS	Geoloc Systems	France
11	RWTH	Rheinisch-Westfaelische Technische Hochschule Aachen University	Germany
12	UNIROMA3	University of Roma Tre	Italy
13	COMM	Commsignia Ltd	Hungary
14	IRU	International Road Transport Union - Projects ASBL	Belgium
15	SNCF	SNCF	France
16	DLR	German Aerospace Center	Germany
17	UTBM	University of Technology of Belfort-Montbéliard	France

Executive Summary

Deliverable D3.1 is the first deliverable of the Work Package 3 (WP3). This deliverable aims to describe the proof of concept on data acquisition platform for risk evaluation (task 3.1) and Automatic Incident Detection (AID) system (composing task 3.2). A global architecture (hardware and software) is built in order to receive, manage, process the data collected in the different test sites. This part of the work focuses in the collection of video data for the development of several systems and particularly the risk evaluation and AID systems. The main objective is to verify that these data, coming from different places, with very different formats, with different acquisition rates, different image sizes, are suitable for the detection and recognition of potentially dangerous situations at level crossings.

This document provides the risk evaluation and AID systems objectives, and describes the possibility for the two systems to share the same datasets. Firstly, the initial datasets gathered are presented and preliminary results on some of the scenarios are shown using the AID system. Obstacle stuck on the LC, atypical behaviour on the LC, detection of a traffic jam, presence of a pedestrian on the LC are the few of the pre-selected scenarios taken into account.

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1. INTRODUCTION

1.1 Objectives of SAFER-LC project

Over the past few years, there has been one death and close to one serious injury every day on level crossings in Europe. Therefore, SAFER-LC aims to improve safety and minimize risk by developing a fully integrated cross-modal set of innovative solutions and tools for the proactive management and design of level-crossing infrastructure. These tools will enable road and rail decision makers to find effective ways to detect potentially dangerous collision situations at level crossings, prevent incidents at level crossings by innovative design and predictive maintenance methods, and mitigate the consequences of incidents/disruptions due to accidents or other critical events.

The project will focus both on technical solutions, such as smart detection services and advanced infrastructure-to-vehicle communication systems, and on human practices, to adapt infrastructure design to end-users and to enhance coordination and cooperation between different stakeholders from different transportation modes. The project will first identify the needs and requirements of rail-road infrastructure managers and LC users and then seek to develop innovative smart detection and communication systems to adapt them for use by all types of level crossing users. A series of pilot tests across Europe will be rolled out to demonstrate how these new technological and non-technological solutions can be integrated, validated for their feasibility and evaluated in terms of their performance.

The project will deliver a bundle of recommended technical specifications (for standardisation), human practices and organizational and legal frameworks for implementation.

Finally, SAFER-LC will develop a toolbox accessible through a user-friendly interface which will integrate all the project results and solutions to help both rail and road managers to improve safety at level crossings.

1.2 Acronyms

AID – Automatic Incident Detection
ATX – Advanced Technology Extended
CUDA – Computer Unified Device Architecture
GPU – Graphics Processing Unit
LC – Level Crossings
IP – Internet Protocol
NAS – Network Access Storage
POE – Power Over Ethernet
RSU – Road Side Unit
SDK – Software Development Kit
SPF+ – Small pluggable form-factor
UPS – Uninterruptible Power Supply

1.3 General description

This deliverable is a proof-of-concept on data acquisition platform to be used both for risk evaluation system (Task 3.1) and AID systems (Task 3.2). The objective of the risk evaluation system is to identify and understand the dynamics of the development of hazardous situations in LC environments. Oppositely to manual diagnosis performed (by specialized human agents) through punctual field investigations and observations, the task aims to offer an extended version of the temporal dimension of this diagnosis by exploiting automatically big databases provided by video system installed in LC for acquiring video sequences over long periods (several weeks). The developed off-line automatic video analysis system will allow to refine/correlate human diagnosis with quantitative information (statistics and classification) extracted from the automatic system, and to extract behavioural models of user-to-user and user-to-infrastructure (LC) interactions. Although this problematic is widely addressed by researchers in different contexts, it constitutes a niche of open questions with scientific and technological locks. Indeed, there is no generic user behavioural model for a given context, since it is necessary to take into account specificities (physic and socio-demographic) of each environment of the context, including the variety of users. To our knowledge, there is no prior research work focusing on behaviour model extraction in a level crossing context. Furthermore, most research related to user behaviour modelling are focused on one type of users (pedestrian, vehicle) and one type of behaviour (transgression for example) while user behaviour depends generally on interactions.

The objective of the smart detection system (Task 3.2) is to develop a warning system based on intelligent detection of potentially dangerous situations occurring at LCs and some hazardous situations in the larger surrounding of the LC. An optimized Automatic Incident Detection (AID) dedicated to level crossings will be specified, implemented, and evaluated. This subtask will use of recommendations and a list of requirements that will be outlined as part of WP1. The AID system allows for the accurate detection of hazardous events and localization of obstacles which are motionless or in motion at the LC that could jeopardize the safety of LC users especially vulnerable users. Possible events to detect include vehicles stopped on the tracks, objects left on the tracks, trespassing and pedestrians stopping or crossing the LC.

The same data collected from the fields is shared for the two tasks (Task 3.1 and 3.2) included in the same Work Package. For the risk evaluation, some simulations scenarios will be developed representing potentially dangerous situations at LC. The simulations are fed and modelled by using real data coming from the test sites (real level crossing or mock-up built for this purpose). Automatic Incident Detection, also called Smart Detection System, is planned to detect and recognize, in real time, dangerous situations from the collected real time data. The purpose of this deliverable is to identify the datasets already existing which can be shared by the two tasks, as well as to collect additional datasets to feed the two systems.

1.4 Interactions with other tasks and evolution within the project

The work included in this deliverable, concerning tasks 3.1 and 3.2, is strongly linked to task 3.4 of the communication system. The main aim of Task 3.4, Communication systems for cross-modal information sharing, is to transmit the information generated at the level crossing by video system and to send alarms to different actors around the LC depending on the event detected. Risk and hazardous information as well as dangerous situation should be sent to the approaching cars, the approaching train or to a control centre. The nature of information and whom to send the information will be developed between tasks 3.1, 3.2 and 3.4. The AID system will be connected to the communication system using a specific interface. This work is in progress

1.5 Structure of the document

Introduction and general description of the deliverable is given on section 1. Section 2 contains the description of the data sets collected so far. Sections 3 and 4 discuss the developments of the risk evaluation system and the AID system, respectively. Preliminary results of some scenarios are given in section 5, which is followed by a Conclusion and perspective of the work section.

2. DESCRIPTION OF THE DATASETS COLLECTED

2.1 Objectives

The aim of this work is to illustrate that the datasets gathered are suitable to the architecture under development. Part of the work is to collect as much video data as possible from different test sites and to process them by the risk evaluation and AID systems. By that to show the feasibility between dataset and architecture. The compatibility between dataset and architecture is tested based on predefined scenarios representing potentially dangerous situations at level crossings. The feasibility is shown later in this document.

2.2 Video data collected

There are several sources of data which are used within the project at the moment. Dataset coming from the Internet with an existing ground truth is shown in Figure 1. These datasets are used by researchers to compare their video algorithms. These datasets represent many different scenes with scenarios including cars, pedestrian and trucks during very different weather conditions. They are very useful to test the performances of some video algorithms.

Figure 2 shows data coming from a past project, belonging to a French work programme, called PANsafer. The datasets are coming from Mouzon, in the north of France which is a rural area from Lausans, with several urban level crossings. Data coming from a real level crossing in the Toulouse region called Montaudran is shown in Figures 3 and 4. However, datasets to be collected from two level crossings are awaiting for an authorization. The Montaudran LC is a semi-urban LC, with a curved trajectory and with a very heavy traffic including cars, two-wheels, pedestrians and a high frequency for trains.

Data coming from a mock-up built at Cerema Toulouse premises is shown in Figures 5, 6 and 7, in which the different scenarios are played. A further detail can be seen in this document.

Figure 1: Intersection roads/trams

Figure 2: Mouzon test site

Figure 3: A first view of the Montaudran level crossing

Figure 4: Another picture shot at Montaudran test site

Figure 5: Mockup level crossing installed at Cerema Toulouse

Figure 6: Mockup level crossing installed at Cerema Toulouse with a pedestrian and bicycle crossing the LC at the same time

Figure 7: Mockup level crossing installed at Cerema Toulouse. A big truck zigzagging while the barriers are closed.

3 DEVELOPMENT OF THE RISK EVALUATION SYSTEM

The risk evaluation system is an offline process that uses one or several videos as input and analyse them to detect dangerous or abnormal behaviours and the events leading to them. The system architecture is developed by the project partner UTBM. This section describes the architecture of the developed simulator which can generate realistic videos in the absence of real video data recorded in a level crossing (LC). Details on how the collected datasets can be used to validate, train and fine tune the developed algorithms are given.

3.1 Architecture of the Risk Evaluation System

The risk evaluation system processes video data offline in a fully automatic way. It is composed of a set of distinct modules in order to extract the user behaviour models and useful information in a sequential fashion. The detailed block diagram of the system is shown in Figure 8 [1, 4].

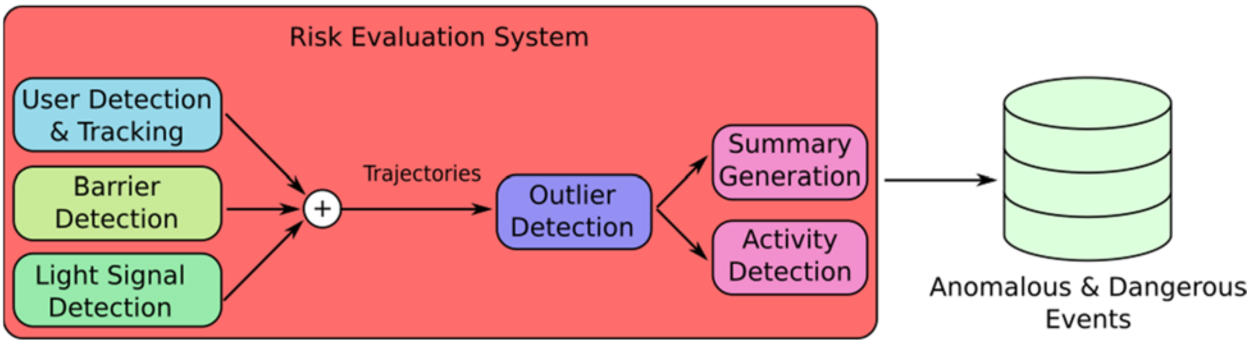

Figure 8: Overview of the architecture of the Risk Evaluation System

The input of the system is video data captured by one or multiple cameras. The output is a database containing the dangerous situations detected in the video as a human-readable summary along with any relevant information (e.g. date/time of occurrence, number of actors, type of actors, space-time trajectories of the involved actors, etc.). The database can be queried to extract statistics about the LC in order to assess its level of dangerousness. In the context of this system, a situation is defined as an ordered set of discrete activities or actions that may or may not be dangerous in themselves.

The pre-processing modules analyses the input video in order to detect the infrastructure-related events (traffic signal state, barrier state, etc.) and LC users, classify the users (pedestrian, car, truck, etc.), and extract their space-time trajectories. Trajectories and infrastructure events are subsequently combined in order to analyse activities in the context of the LC.

An outlier detection module [5] is executed on all the collected trajectories to retain only the anomalous behaviours, which are then sent to the two core modules. The first detects occurring activities by analysing the trajectories of the users, while the second automatically generates a semantic description using verbs corresponding to these detected activities and adjectives corresponding to actor states. These data are then organized in a database for convenience.

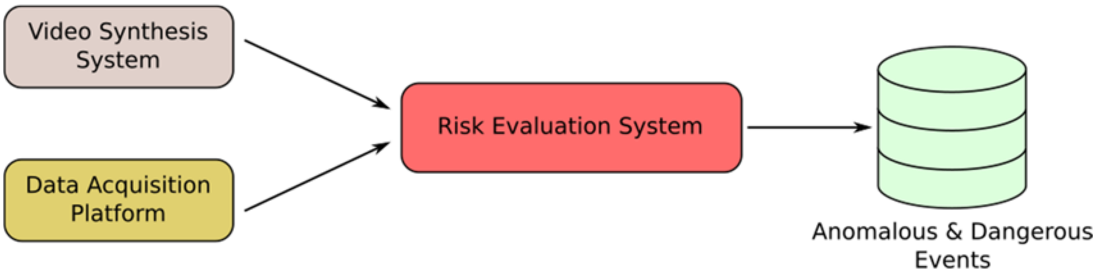

Figure 9: Data sources for the Risk Evaluation System

The Risk Evaluation System is designed to use two sources of data, namely synthetic video and real video data, while the latter coming from the data acquisition platform, as shown in Figure 9. The next sections will provide the combination between real and synthetic data and the way they are used in the processing platform [2].

3.2 Video synthesis system

To get around the lack of real data (long-term video data acquired from real LC), a video synthesis system has been developed. This system is composed of a high-resolution renderer, an agent-based behavioural simulator and a complex lighting and weather simulation system. The block diagram of the video synthesis system in relationship with the risk evaluation system is illustrated in Figure 10.

Figure 10: Overview of the complete architecture using the video synthesis system as input of the risk evaluation system.

3.2.1 High-resolution renderer

The video synthesis system uses the real-time 3D game engine Unity to produce images that are encoded in a video. This engine includes a physics engine that is used to simulate the dynamics of road vehicles. A 3D model of an existing or fictitious LC is used as a basis for the scene in which one or more virtual cameras can be installed. An example of real world LC modeled in the engine can be seen in Figure 11. Normal LC operations can be simulated by animating the representation of the traffic lights and barriers.

Figure 11: Example of real world LC modelled in 3D in the Unity engine.

3.2.2 Agent-based behavioural simulation

The video synthesis system uses an agent-based urban mobility simulator, in which pedestrians and road vehicle drivers are modelled as autonomous agents capable of perceiving their environment and acting independently or cooperatively to achieve their predefined goals.

This modelling is used to simulate various normal behaviours but also some dangerous behaviours. For example, an agent can be programmed with an impaired perception that reduces the likelihood it will detect the traffic lights of the LC or the closing barriers. It can also be programmed to attempt to cross the LC even if the traffic lights are on.

The behavioural simulation coupled with the physics engine can also be used to simulate dangerous situations caused by the dynamics of the vehicle, either under extreme weather conditions (heavy rain or snow) by adjusting the tire friction coefficient, or due to mechanical malfunctions (stalling, brake failure, etc.).

3.2.3 Lighting and weather simulation

In order to generate videos under different lighting and weather conditions, a module has been developed to simulate the weather using physically based models for the color of the sky, the clouds and the wetting of the road when it rains [3]. Figure 12 shows a simulated LC under various lighting and weather conditions [6].

Figure 12: Example of simulated LC under various lighting and weather conditions. (Top left: sunny, top right: rainy, bottom left: heavy rain, bottom right: night)

3.3 Usage of real data from the data acquisition platform for Risk Evaluation

The real data sets, taken from the data acquisition platform, can be used in numerous places in the risk evaluation system. The first usage is to illustrate some dangerous behaviours that can be studied and modelled in the simulator. The second one is to validate the effectiveness of the detection and recognition algorithms on real world data. Finally, the third usage is to train the deep-learning algorithms to improve accuracy on real world data.

3.3.1 Usage for the simulator

Collecting real world data is useful as a pre-process for the simulation. It is often quite difficult to know how to write the rules of the behaviours of the agents in order to produce specific emergent behaviours in the system. Therefore, it is necessary to visualise and analyse real situations in order to propose their models.

Moreover, once a behavioural model is proposed, it must be fine-tuned to be representative of a class of observed real world behaviours. Most behavioural models use a large set of parameters that define how each agent acts in a specific situation (preferred speed and acceleration, reaction time, distribution of planned objectives, etc.) and in most cases, it is difficult to guess the appropriate value of these parameters without a reference. With the usage of collected real data sets, it is possible to perform analysis of the behaviours observed in one or several real videos of a single LC to derive the values of the parameters in order to reproduce the same behaviours in a statistically representative manner.

3.3.2 Usage for the validation of the algorithms

Since most detection and recognition algorithms in the risk evaluation system are trained on synthesized data, they must be tested against real world data in order to validate the system in a real use case. There is no priori guarantee that the detection/recognition algorithms will perform well on real images compared to images coming from the simulator, even if they appear very similar to human eye. Some algorithms may be sensitive to image grain or texture patterns that are difficult to distinguish by the human eye.

3.3.3 Usage for the training of the algorithms

Training the detection and recognition algorithms requires large and heterogeneous data sets so this can cause a problem when using only synthesized images. Indeed, it is difficult to generate a wide diversity of appearances for the objects (mainly cars, trucks and pedestrians) as it requires to produce a 3D representation for objects or variant of objects. This process is time consuming and requires a specific skill-set. Therefore, it is common to insert real-world images along with the synthesized ones in the training sets of deep-learning algorithms. By using the collected real data sets, the algorithms within the risk evaluation system may be more generalized and consequently less prone to false positives/negatives or misclassification.

4 DEVELOPMENT OF THE AID SYSTEM

The main aim of this section is to verify that the video detection and recognition of dangerous situations is compatible with the video data gathered. For that, "smart algorithms" are developed that able to recognize some dangerous scenarios. These algorithms are applied on the available datasets. In this section, the architecture of the developed system and its main functionalities will be described in detail, and how the datasets gathered fit well with the developed tools will be explained.

4.1 Hardware architecture of the acquisition and processing system

4.1.1 Hardware components

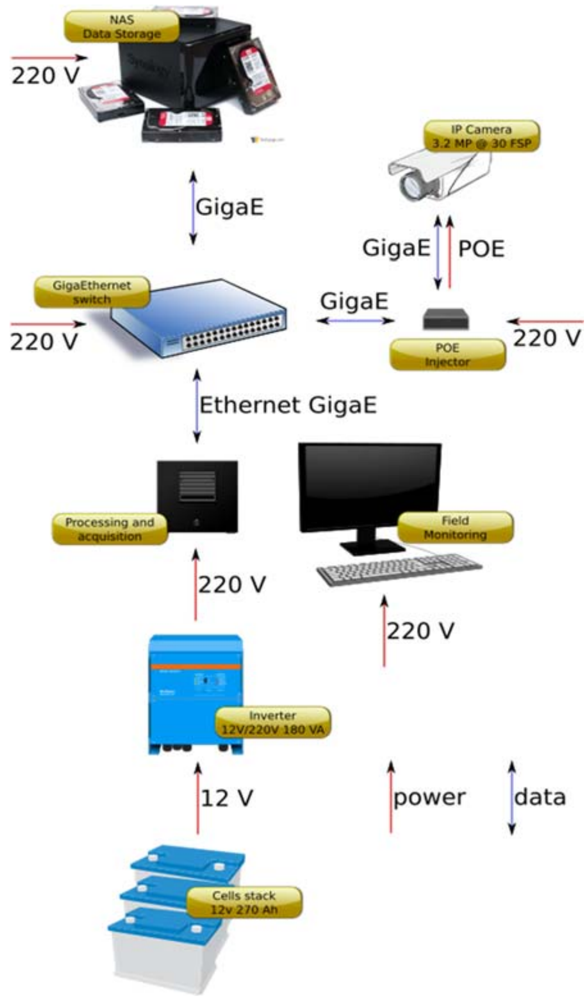

Figure 13: Smart Detection hardware architecture

The main component used in the smart detector proof of concept architecture shown in figure 13, is the processing and acquisition unit. This equipment is based on a mini ATX (Advanced

Technology Extended) Personal Computer platform. This choice was essentially justified by the fact of being able to integrate a GPU (Graphics Processing Unit) card, allowing the execution of processes using the CUDA (Computer Unified Device Architecture) cores that these cards are equipped with, such as Deep Learning. This architecture is therefore generic enough to test various technological solutions.

The processing and acquisition unit is contained in a case whose dimensions are between 26x26x20 cm. The selected dimensions enable the equipment easy to move in the fields and the test sites.

The second essential component of the hardware architecture is of course the acquisition camera. The choice fell on an IP (Internet Protocol) camera powered by POE (Power Over Ethernet) technology. The criteria adopted at this point were the universal and standardised aspects of these technologies. Indeed, as defined in next sections, the idea was to develop processing and analysis tools that are compatible with different operating systems (such as Windows or Linux). However, the connectivity by Ethernet is the one that offers the most ease on this field.

The selected camera comes with an optical system which is able to detect objects situated in close proximity to the pole. However, the optical field is large enough in order to observe at a glance, the entire crossing plank and the nearest roadways. The camera sensitive assets parts are protected by a protective case compliant with the EN 60529 IP65 level.

A NAS (Network Access Storage) unit was added to the proof of concept architecture. This unit is used to store videos and pictures data in order to retain background information of the ground truth if needed. This equipment could host 5 Hard Disk Drives. We choose some 10 TB (terabytes) Disks. Thereof, the total NAS capacity is about 50 TB. The data speed capacity between the processing and acquisition unit and the NAS unit can be improved, thanks to an incorporated optical 10 Gb SPF+ (Small pluggable form-factor) card.

Finally, as some components needs a standard 230-volt electric power in order to operate, a cells stack was added in order to power all the other equipment in case of test on field without a AC Power Supply outlet. The batteries 12-volt power is converted to 230-volt by means of a power inverter. An UPS (Uninterruptible Power Supply) unit is added for the purposes of stop correctly the processing and acquisition unit, in case of lack of power in the cells stack. The battery pack is designed and sized for allow the entire smart system detection proof of concept architecture, proper functioning for at least one day.

4.1.2 Intercommunication between the components and outside

As described previously, the intercommunication between the components, is ensured by a gigabit Ethernet link. The processing and acquisition unit is equipped with two-gigabit Ethernet socket. Therefore, it is possible to separate the communication between communication general standard equipment (like communication system with outside of smart detection system for example) and the specific gigabit Ethernet link dedicated for the communication with the camera (the acquisition link). This kind of hardware solution allows to improve the streaming video flow quality.

The communication outside the smart detection system is provided by a gigabit Ethernet link. This allows communications with the RSU (Road Side Unit) situated in close proximity to the line crossing.

4.1.3 Link with the software application (Libraries)

The software architecture includes a specific layer dedicated to the communication between the processing and acquisition unit and the camera, through the gigabit Ethernet acquisition link.

This layer uses two pieces of software:

- Smartek proprietary camera manufacturer SDK (Software Development Kit) for Linux and Windows operating systems
- Aravis open source library for video acquisition using Genicam cameras.

Both solutions implement the gigabit Ethernet protocols used by the selected camera. Aravis software offers the capability to reduce the dependency with a specific manufacturer's camera but is only Linux operating system compliant. However, this downside can be offset by the fact that Linux supports directly tools commonly used in data sciences, making it the reason why we finally choose this operating system for the processing and acquisition unit.

4.2 Architecture of the software application

Following the previous description of the hardware architecture managing the flows of video data, the software architecture is presented in the following sections.

4.2.1 Synoptic of data acquisition and processing

The synoptic of data acquisition and processing is composed of three components:

- Detection of novelties occurring in the images processed (car crossing, presence of a new pedestrian, a new object, etc.)
- Tracking of the new object to analyse its "behaviour"
- Recognition of a possible dangerous scenario (car stopped, existing of s small jam, etc.)

This synoptic is illustrated in Figure 14 and this interface could be a future application for the transport operators to work with if the system is integrated in the operation loop of the LC.

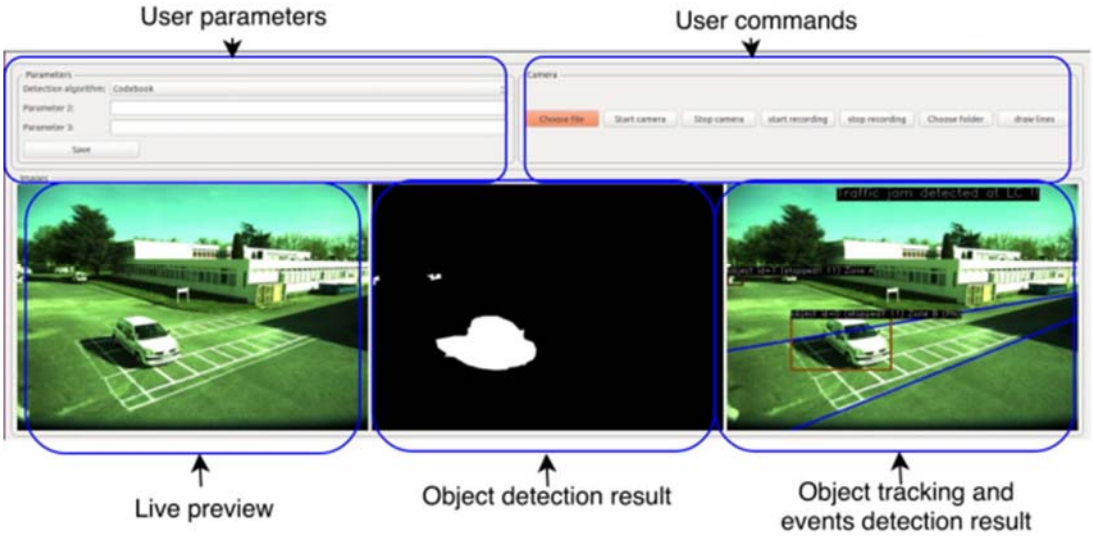

Figure 14: Software configuration of the different steps of the processing chain

4.2.2 Main functionalities for the application: acquisition, post processing and live processing

Acquisition

This functionality allows the user to work in "acquisition mode" that is to say capturing frames at a given frequency (30frames/second) and store them on a hard disk to process them later;

Post processing

Once the previous data collected is stored, the system is able to process the data in an off-line way.

Live processing

The application processes the captured frames in real time, and simultaneously saves them with a self-erasing buffer of a given duration. When an event occurs, the application starts recording frames. This functionality is very useful when unexpected accidents occur: we gain the images of the crash plus what happened during the minutes before thanks to the data included in the buffer.

Live processing and acquisition

This functionality is two-fold: Acquisition of data and real-time processing. The real-time processing will inform the scenario's recognition and the data gathered will play the role of ground truth in order to measure the performances of the system.

4.2.3 Processing of the collected data

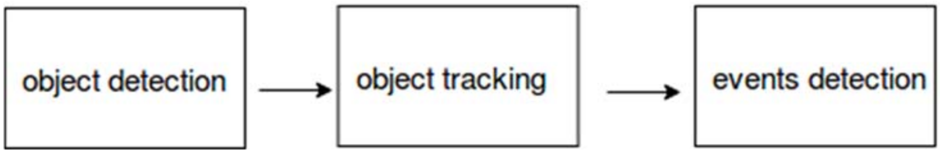

Figure 15: Processing chain blocks

As illustrated in Figure 15, the processing contains three main blocks:

Object detection:

This consists of detecting boundaries of moving objects (vehicles, pedestrians, etc.) in each frame. We are developing a list of available detection algorithms. Then, according to the type of events and configuration of the LC, the user will be able to choose the suitable algorithm for object detection.

Object tracking:

If one or several objects could be detected, the application is able to track them in consecutive frames. The application assigns an Id to each tracked object.

Examples of events detection:

Based on the objects trajectory, some events can be detected. Some examples are given below:

- If an object is stopped at LC, an alert **"stopped cars"** is identified and reported, either to the control centre, to the approaching cars or to the train, depending on the management system of given railway system.

- If many objects are stopped near the LC, an alert **"traffic jam"** is identified and reported

- If an object crosses the LC and then moves back, an alert **"atypical behavior"** is detected.

4.3 First pre-selected scenarios

4.3.1 Description of the collected data and their usefulness

The first algorithms under development within task 3.2 are applied on datasets gathered in Cerema premises. Indeed, with the mock-up built in Cerema, it is possible to play many scenarios imagined or coming from real accidents occurring at LC and mentioned in Deliverables D1.2 and D1.3.

The scenarios played are carried out when the barriers are closed or opened. One will find hereunder a summary of the scenarios that we aim to process, the details are included in Annex 1.

<u>The scenarios when the barrier is opened:</u>

- Vehicle stopped on decking, open barriers, normal arrival
- Vehicle stopped on decking, open barriers, slow arrival
- Vehicle stopped on decking, open barriers, arrival with braking (surprise effect)
- Vehicle stopped on decking, open barriers, with a strange trajectory (alcoholic)
- Vehicle stopped on decking, open barriers, fast arrival
- Crossing the LC at different speeds
- Speed variation approaching the LC then restart
- Speed variation approaching the LC then restart
- Vehicle crosses the LC halfway and then moves back
- Oblique crossing of the LC
- Simulation of traffic jams
- Car involuntarily blocked by another
- Normal crossing of vehicle and pedestrians using LC
- Progressive pedestrian arrivals on the LC
- Pedestrian fall on the LC
- Pedestrians crossing the LC

<u>The scenarios when the barrier is closed:</u>

- Zigzagging
- Zigzagging (motorcycles and bicycles)
- Evolution of a pedestrian or several along the way
- Fast crossing of a pedestrian closed barriers
- Slow crossing of an old pedestrian
- Crossing an alcoholic
- Emergency exit from the vehicle

4.3.2 Selection and processing of key scenarios so far

In the framework of this deliverable, the processing chain when dealing with the following scenarios are chosen for illustration:

- An obstacle present at the LC
- Atypical behaviour on the LC
- Traffic jam
- Presence of a pedestrian on the LC

5 FIRST RESULTS FOR CHOSEN SCENARIOS

5.1 An obstacle at LC

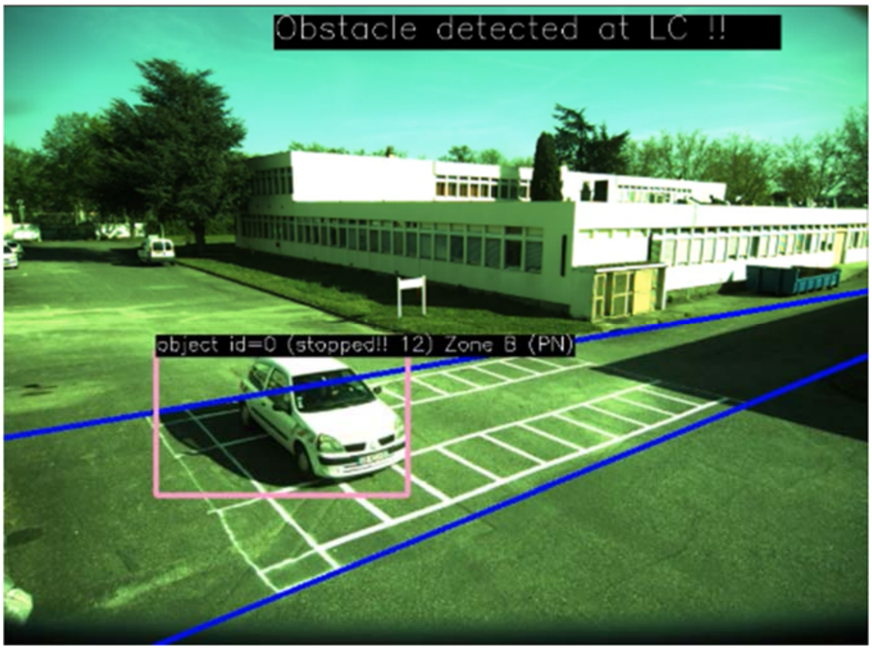

Figure 16: Detection of a car stopped on the LC

The system detects and tracks all types of vehicles. When a vehicle is stopped at LC zone, a timer is started. When the timer reaches a threshold, an alert “Obstacle detected at LC” is sent to the communication system as seen in Figure 16.

5.2 Atypical behaviour

When a vehicle crosses the LC zone and then moves back to the zone that it came from, an alert “Atypical behaviour at LC” is sent to the communication system as seen in Figure 17. This scenario was asked by a project partner SNCF as an example. [7, 10]

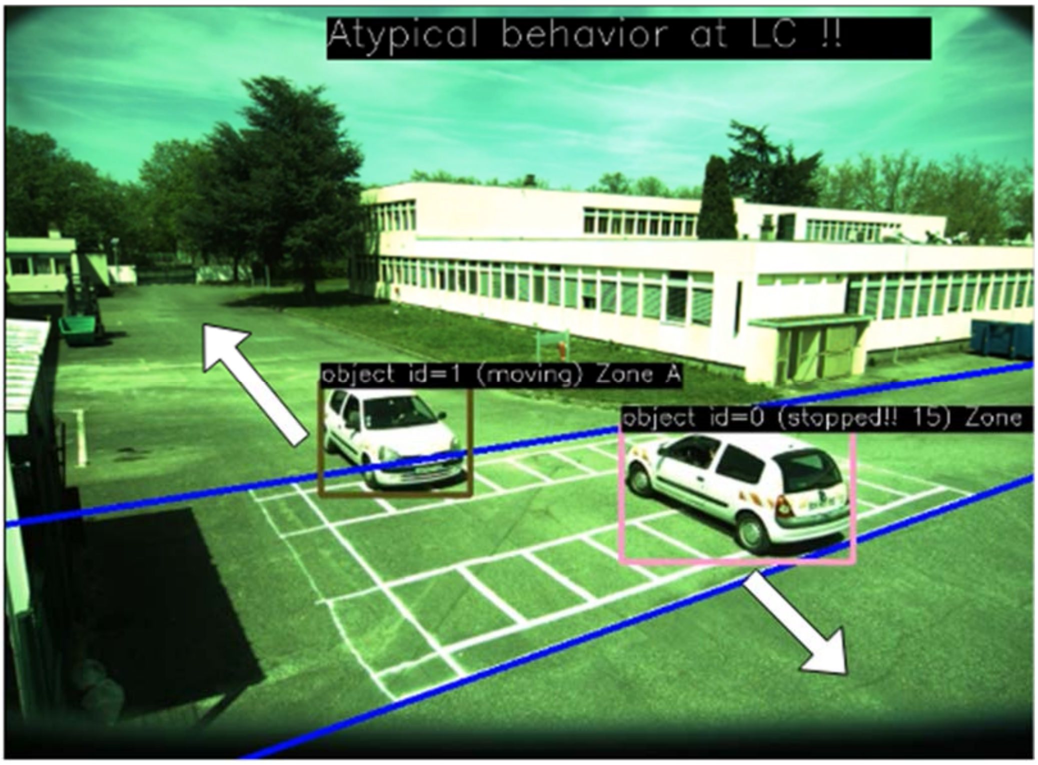

Figure 17: Atypical behavior at the LC

5.3 Traffic jam

When barriers are open and there are many vehicles stopped near the LC, the last arrived vehicle could be blocked at LC. Thus, when such a scenario is presented, the system sends an alert to the communication system “Traffic jam detected at LC” as an example, as seen in Figure 18. [7] [10]

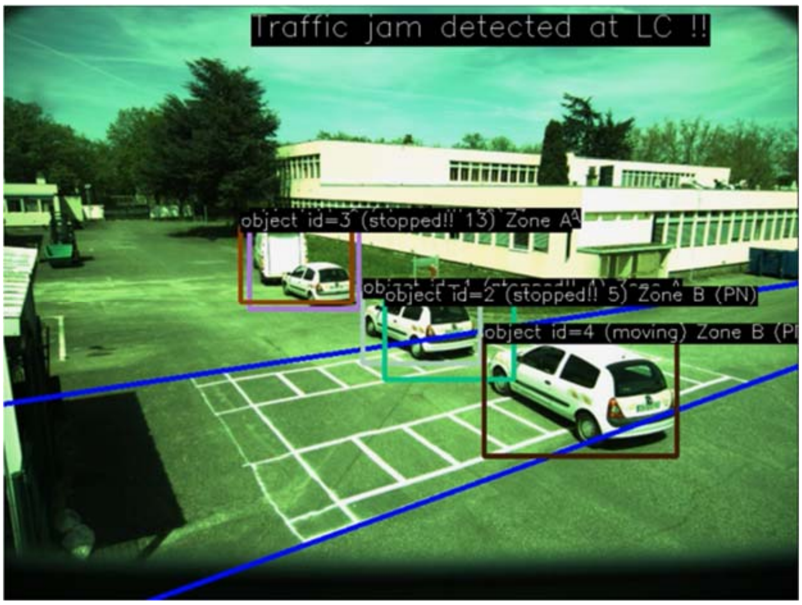

Figure 18: Traffic jam at the LC

5.4 Pedestrian at LC

The system detects and tracks pedestrians. When barriers are closed, and pedestrians are crossing, an alert is sent to the communication system "Pedestrians at LC", see Figure 19. [7, 10]

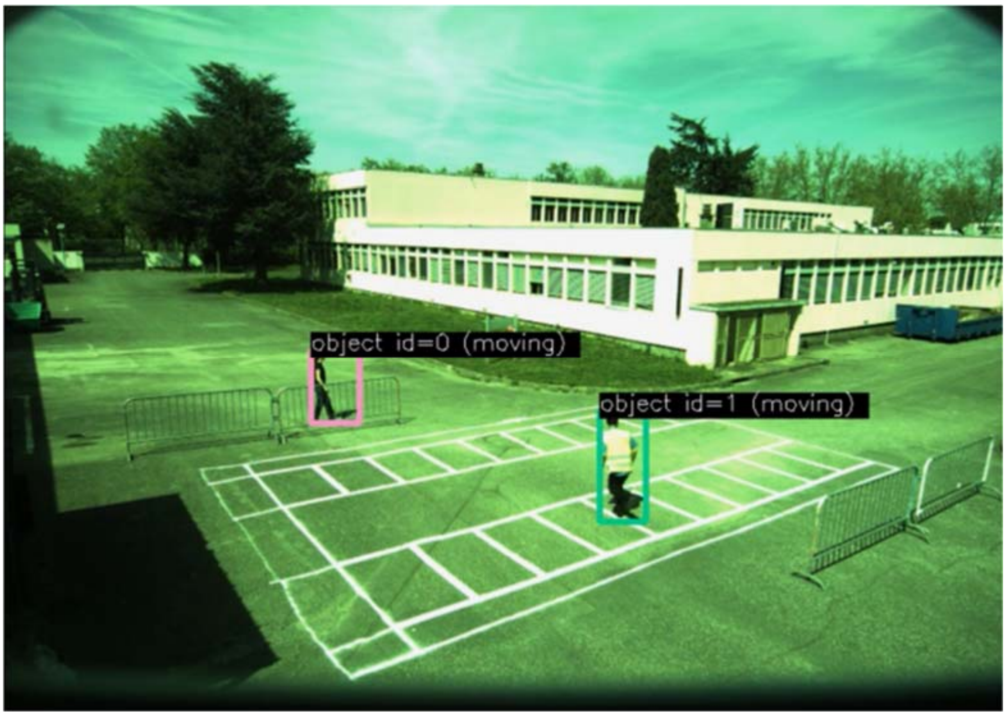

Figure 19: Pedestrians crossing the LC while the barriers are closed

An example concerning Mouzon test site in the north of France, is detecting vehicle stopped at the LC as seen in Figure 20. [8]

An example of two pedestrians clearly detected when crossing the LC processed by the smart detection system. The detection is based on Lucas Kanade algorithm [9]. The image is coming from Lausans test site (urban LC), see Figure 21.

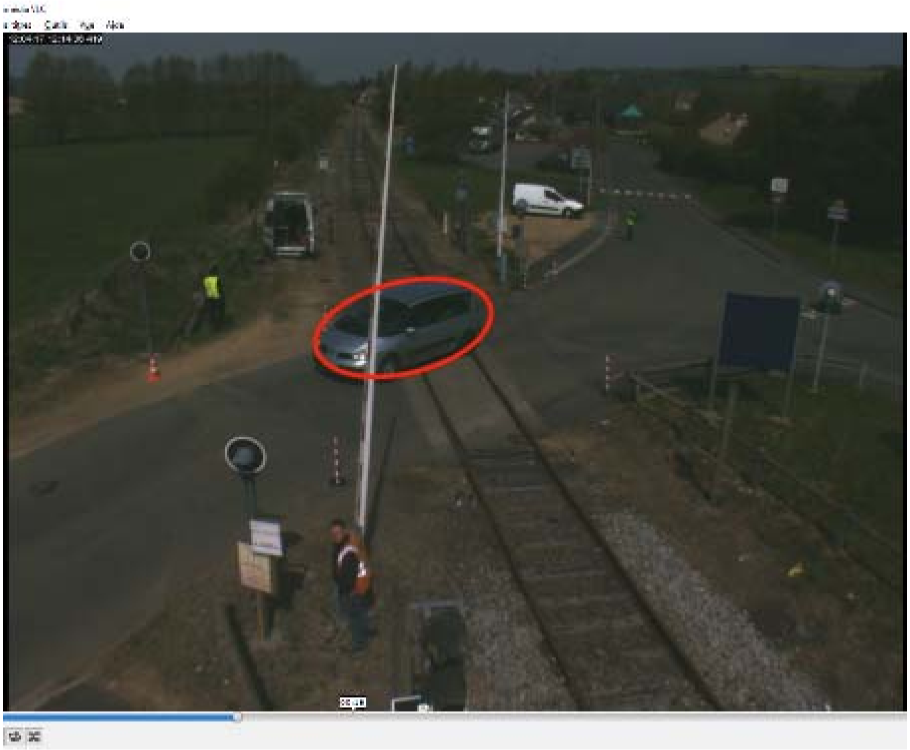

Figure 20: Detection of a stopped vehicle at Mouzon LC

Figure 21: Two pedestrians clearly detected when crossing the LC.

6 CONCLUSIONS AND NEXT STEPS

In this Deliverable, the "*Proof-of-concept for data acquisition platform for risk evaluation and AID systems*" and the data available for the task 3.1 and 3.2 so far are presented. The organization in terms of hardware architecture and software architecture of the existing datasets so far is also discussed. Some very preliminary results are presented. The first algorithms implemented show the good choice of architecture. Indeed, the developed algorithms are suitable to the type of data used whatever their origin: real data or synthetic data. The next stage is to obtain additional datasets of other real LC(s) and to complete the scenarios imagined through discussing with transport operators like SNCF in order to fill the gap between the planned scenarios and the needs of the operator(s).

In the meantime, the development and improvement of the risk evaluation and the AID systems is continued by adding additional scenarios, improving the software development and implementation in the hardware architecture to show the compatibility between architecture and data processed.

For evaluation and test sites purposes, very close collaboration is undergoing with the teams of Task 3.4 (Communication and data sharing). The global chain detection, diagnosis on the situation of the LC and communication will be demonstrated in Aachen test site. Indeed, the video system will be interfaced with the communication system in order to send all kind of data (detection, numerical data, alarms, video, etc) between the LC and the road vehicles, the train and a control centre. This part of the work is in progress.

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ANNEXE 1 SCENARIOS OF CEREMA DATASETS

OPEN BARRIERS

Scenarios: one vehicle, open barriers, stopping at LC

		Description	Drivers Guillaume (Kangoo)	Chafik (Clio)	Jean-Paul(Van)	Philippe (Kangoo)	Cedric ?	LK (Clio)	trucks ?	
									Message to send	Type of message
Vehicle stopped on decking, open barriers, normal arrival	Stop 5s	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times		
	Stop 15 s	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times		
	Stop 30 s	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times		
	Stop more than 2 mn	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times		
Vehicle stopped on decking, open barriers, slow arrival	Stop 5s	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times		
	Stop 15 s	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times		
	Stop 30 s	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times		
	Stop more than 2 mn	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times		
Vehicle stopped on decking, open barriers, arrival with braking (surprise effect)	Stop 5s	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times		
	Stop 15 s	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times		
	Stop 30 s	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times		
	Stop more than 2 mn	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times		
Vehicle stopped on decking, open barriers, with a strange trajectory (alcoholic)	Stop 5s	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times		
	Stop 15 s	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times		
	Stop 30 s	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times		
	Stop more than 2 mn	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times		
Vehicle stopped on decking, open barriers, fast arrival	Stop 5s	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times		
	Stop 15 s	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times		
	Stop 30 s	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times		
	Stop more than 2 mn	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times		

Scenarios: one vehicle, open barriers, without stopping at LC

		Description	Drivers Guillaume (Kangoo)	Chafik (Clio)	Jean-Paul(Van)	Philippe (Kangoo)	Cedric ?	LK (Clio)	trucks ?
Crossing the LC at different speeds	10 km/h	to arrive in a far way	5 times	5 times	5 times	5 times	5 times	5 times	
	25 km/h	to arrive in a far way	5 times	5 times	5 times	5 times	5 times	5 times	
	35 km/h	to arrive in a far way	5 times	5 times	5 times	5 times	5 times	5 times	
	50 km/h	to arrive in a far way	5 times	5 times	5 times	5 times	5 times	5 times	
Speed variation approaching the LC then restart	To arrive at very high speed then clear braking and restart	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times	
Speed variation approaching the LC then restart	To arrive at very high speed then clear braking and restart	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times	
	Stop 15 s	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times	
	Stop 30 s	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times	
	Stop more than 2 mn	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times	

Scenarios with one or more vehicles moving forward and backward

		Description	Drivers Guillaume (Kangoo)	Chafik (Clio)	Jean-Paul(Van)	Philippe (Kangoo)	Cedric ?	LK (Clio)	trucks ?
Vehicle crosses the LC halfway and then moves back	Two vehicles arrive face to face, stop at the same time at the LC and move back and at the end cross the PN		Kangoo 10 times	Clio 10 times					
Oblique crossing of the LC	Arrival of vehicles at LC with normal speed and oblique crossing of LC		5 times	5 times	5 times	5 times	5 times	5 times	
Simulation of traffic jams	A vehicle normally crosses the LC and then stops 10 m later. It is followed by several vehicles and the last is on the LC (the van creates the trafic jam)		Make 10 scenarios of traffic jams with 2, 3, 4, or 5 consecutive cars						
Car involuntarily blocked by another	A vehicle1 arrives and stops before the LC. The next, vehicle 2 double to pass but at the same time in the other direction another vehicle 3 arrives and blocks the 2. The drivers come out chat for a moment and leave in their car normally					3 times			

Scenarios with vehicles and pedestrians

		Description	Drivers Guillaume (Kangoo)	Chafik (Clio)	Jean-Paul(Van)	Philippe (Kangoo)	Cedric ?	LK (Clio)	trucks ?
Normal crossing of vehicle and pedestrians using LC	Here vehicles normally cross the LC while one or more pedestrians adopt a dangerous behavior	10 crossings	10 crossings	10 crossings	10 crossings	10 crossings			

Scenarios with pedestrians alone

		Description	Drivers Guillaume (Kangoo)	Chafik (Clio)	Jean-Paul(Van)	Philippe (Kangoo)	Cedric ?	LK (Clio)	trucks ?
Progressive pedestrian arrivals on the LC	The first remains 5 s, then is followed by another, then another, etc ..... interactions between pedestrians who can discuss, touch each other	5 different scenes. Vary the interactions	5 different scenes. Vary the interactions	5 different scenes. Vary the interactions	5 different scenes. Vary the interactions	5 different scenes. Vary the interactions			
Pedestrian fall on the LC	A pedestrian falls, the others notice him, go to him, take him out and take him out of the LC	5 different scenes. Vary the interactions	5 different scenes. Vary the interactions	5 different scenes. Vary the interactions	5 different scenes. Vary the interactions	5 different scenes. Vary the interactions			
Pedestrians crossing the LC	Pedestrians arrive alone or with others on the LC and remain a good time (selfies)	5 different scenes. Vary the interactions	5 different scenes. Vary the interactions	5 different scenes. Vary the interactions	5 different scenes. Vary the interactions	5 different scenes. Vary the interactions			

CLOSED BARRIERS

		Description	Drivers Guillaume (Kangoo)	Chafik (Clio)	Jean-Paul(Van)	Philippe (Kangoo)	Cedric ?	LK (Clio)	trucks ?
Zigzagging	bypass barrier at 10 km / h	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times	
	bypass barrier at 15 km/h	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times	
	bypass barrier at 25 km/h	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times	
	bypass barrier at 35 km/h	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times	
Zigzagging (motorcycles and bicycles)	bypass barrier at 10 km/h	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times	
	bypass barrier at 15 km/h	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times	
	bypass barrier at 25 km/h	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times	
	bypass barrier at 35 km/h	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times	
	bypass barrier at 35 km/h stop then restart	to arrive separately	5 times	5 times	5 times	5 times	5 times	5 times	
			5 times	5 times	5 times	5 times	5 times	5 times	
Evolution of a pedestrian or several along the way	The pedestrian arrives, bypasses the barrier and runs along the railway until disappearing from the field of the camera		5 times	5 times	5 times	5 times	5 times	5 times	
			5 times	5 times	5 times	5 times	5 times	5 times	
Fast crossing of a pedestrian closed barriers	A pedestrian passes quickly despite the closed barrier		5 times	5 times	5 times	5 times	5 times	5 times	
			5 times	5 times	5 times	5 times	5 times	5 times	
Slow crossing of an old pedestrian	An old man leaning on a cane crosses the LC		5 times	5 times	5 times	5 times	5 times	5 times	
Crossing an alcoholic	An alcoholic pedestrian crosses the LC in a weird way		5 times	5 times	5 times	5 times	5 times	5 times	
Emergency exit from the vehicle	A car arrives at the LC, stops gradually in the middle and after a while the driver leaves the vehicle and leave the LC		5 times	5 times	5 times	5 times	5 times	5 times	