REPAIRING PEOPLE TRAJECTORIES BASED ON POINT CLUSTERING

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Outline

- **Introduction**
- **Approach proposed**: Learning lost and found zones
  - Offline Training Phase
    - Learning trajectory confidence using annotated trajectories
    - Computing automatically the lost and found zones using training trajectories
    - Defining zone triplets linking entry, lost and found zones
  - Online Testing Phase
    - Repairing lost trajectories based on zone triplets
- **Experimentation**
- **Conclusion and Future work**

Introduction [1]

- There are many methods proposed to track mobile objects (e.g. Using Kalman Filter, particle filters, probabilistic data association).
  - Obtained satisfactory results, but complex and long situations of occlusion are not addressed.
- Some works[1,2] have focused on modelling the scene in order to improve the tracking algorithm.
  - Require full trajectories
  - Cannot handle occlusions
  - Take into account only the shape and size of the objects, as they are detected on the 2D image plane.

[1] Fernyhough et al., *Buxton, B & Cipolla, R (editors) ECCV*, 1996.

[2] D.Makris et al., *IEEE Transactions on Systems*, Man and Cybernetics, 2005.

Introduction [2]

- Our motivation
  - Repairing lost trajectories thanks to a model of the scene.
  - Offline learning of the scene model
  - Propose a general method
    - Be able to model various types of scene
    - Require little a priori knowledge about the scene
- Our Approach
  - Define the confidence value for each trajectory and Filter out noisy trajectories
  - Learning the lost and found zones for a given scene
  - Detect and Repair online the lost trajectories

Introduction [3]

- Input
  - Trajectories obtained from a tracking algorithm
  - Zones where object can enter or leave the scene (Entry zone and Exit zone)
  - 3D Person Model
- Output
  - Trajectories after have been repaired

Offline training_
Trajectory confidence value [1]

Trajectory confidence value is computed by nine features:

1. Entry zone
2. Exit zone
3. Trajectory temporal duration
4. Trajectory spatial length
5. Type frequency: number of times the mobile object is classified as a 'person'.
6. Frailty: number of times that the trajectory is temporally lost.
7. Number of neighbours: neighbouring mobile objects at some special temporal instants.
8. Change-Size frequency: number of times the mobile object changes its size according to a predefined dimension variation threshold.
9. Change-Direction frequency: number of times the mobile object changes spatial direction.

$$CV = \sum_{i=1}^{5}(w_i * f_i) + \sum_{i=6}^{9}(w_i * (1 - f_i))$$

where,

CV = confidence value of the trajectory

w_i = the weight (importance) of feature i

f_i = the value of feature i after normalisation

Offline training_ Trajectory confidence value [2]

- Determine the Feature Weights using Supervised Learning
  - ‘Ground Truth’: defines the confidence value of a trajectory; manually annotated, value in interval [0,1]
    - **Complete trajectory**
    - **Incomplete trajectory**
    - **Unreliable trajectory**
    - **Noisy trajectory**

Offline training_
Trajectory confidence value [3]

- **Complete trajectory (Complete trajec.)**: starts in an entry zone and ends in an exit zone ground Truth ≥ 0.8
- **Incomplete trajectory (Incomplete trajec.)**: does not start in an entry zone or does not end in an exit zone, 0.5 <= ground truth < 0.8

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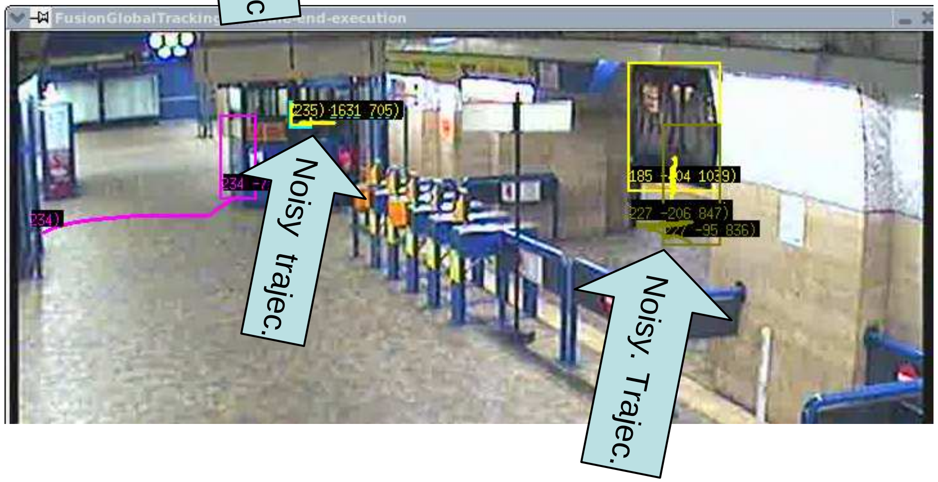
Offline training_
Trajectory confidence value [4]

- **Unreliable trajectory (Unreliable Trajec.)**: does not start in an entry zone and does not end in an exit zone, 0.2 <= ground truth < 0.5

- **Noisy trajectory (Noisy trajec.)**: does not correspond to the trajectory of a person, ground truth < 0.2



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Offline training_ Trajectory confidence value [5]

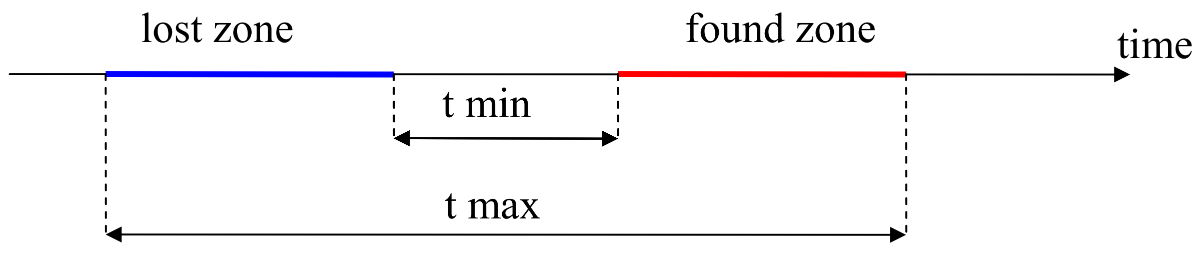
- We optimize the correspondence between ‘Ground Truth’ value and the learned confidence value using **genetic algorithm**.
- Filter out noisy trajectories using the confidence value before learning lost and found zones.

Offline training_
Computing the lost and found zones [1]

- Predefined zones in the scene
  - Entry zone (Start Zone): zone where the object can enter the scene.
  - Exit zone: zone where the object can leave the scene.
- Learned zones in the scene using KMeans clustering
  - Lost zone: zone where the tracking loses usually the objects and differing from exit zone
  - Found zone: zone where the tracking detects usually new objects and differing from entry zone.

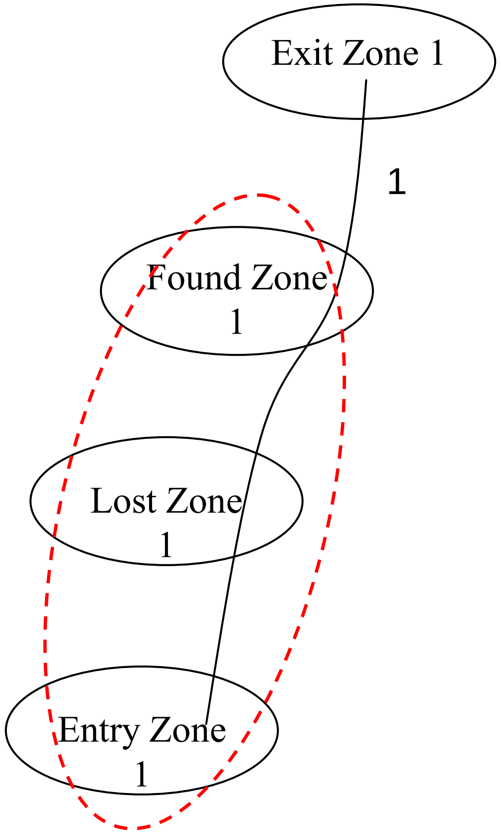
Offline training_
Computing the lost and found zones [2]

- Definition of a zone triplet for a set of trajectories
  - entry zone (EZ)
  - lost zone (LZ)
  - found zone (FZ)
  - ❖ minimum time from lost to found zone (t min)
  - ❖ maximum time from lost to found zone (t max)
- Help the system to online repair the lost trajectories.
- Represent the paths in the scene formed by complete trajectories.

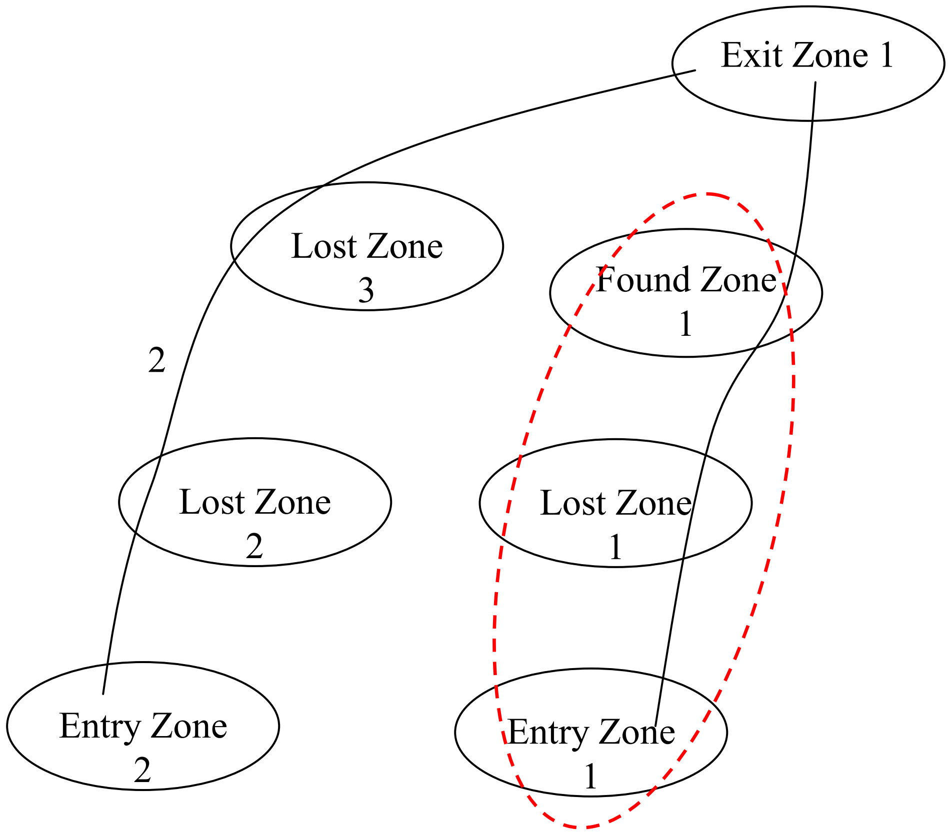


Offline training_
Computing the lost and found zones [3]

- Building zone triplets
  - Only complete trajectories that pass through: ‘entry zone’, ‘lost zone’ and ‘found zone’, are used to construct the zone triplets.
  - Zone triplets ranked (higher priority) by the number of trajectories passing through it.

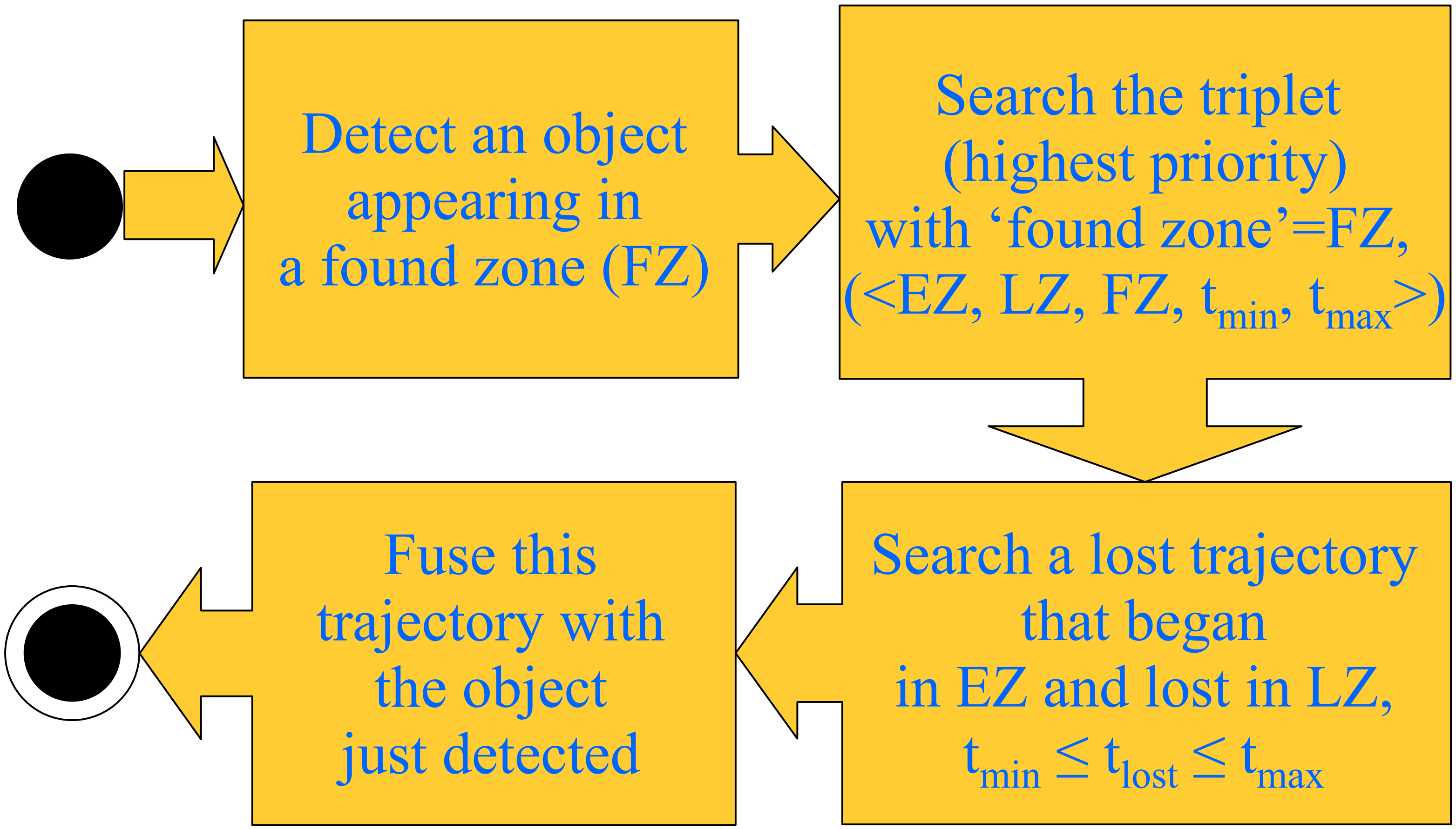


Offline training_
Computing the lost and found zones [4]

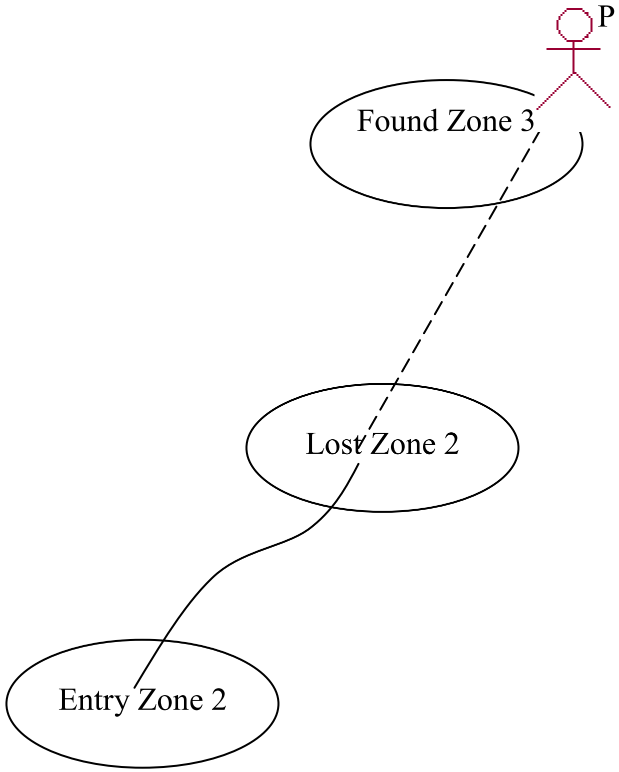


Creation of a zone triplet

Online testing_
Repair Lost Trajectories [1]

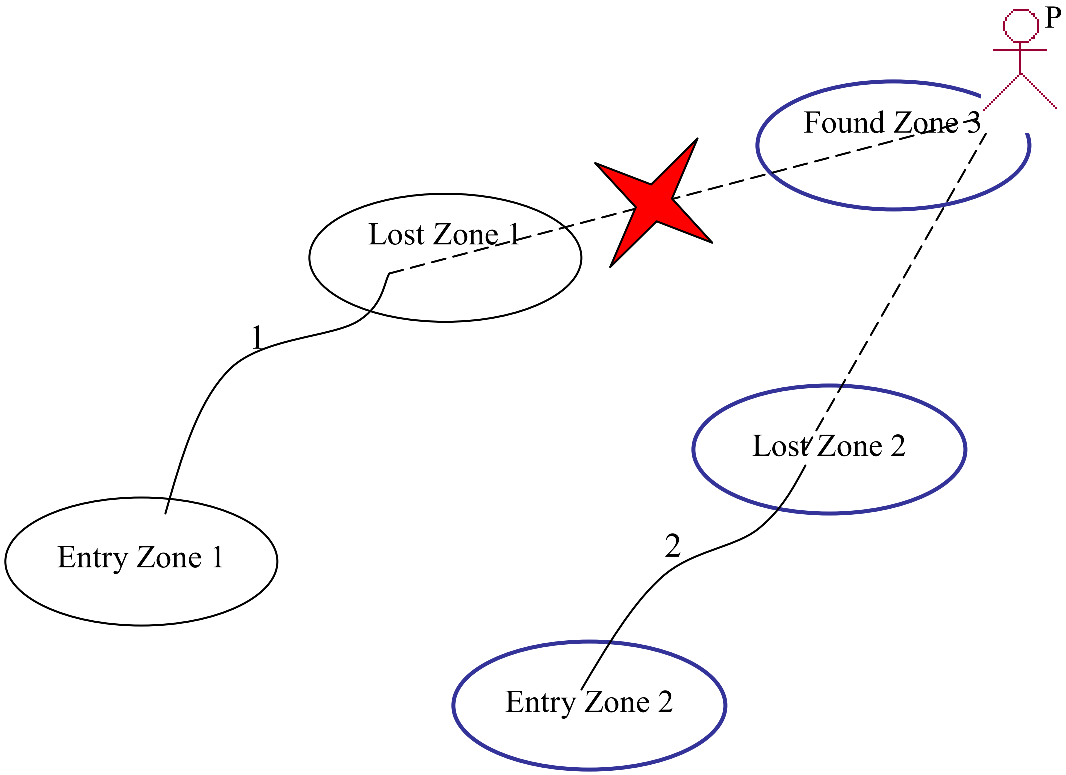


Online testing_
Repair Lost Trajectories [2]



Repairing algorithm

Online testing_
Repair Lost Trajectories [3]



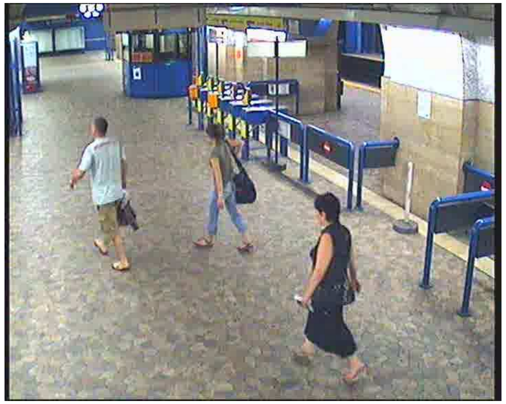
Repairing algorithm

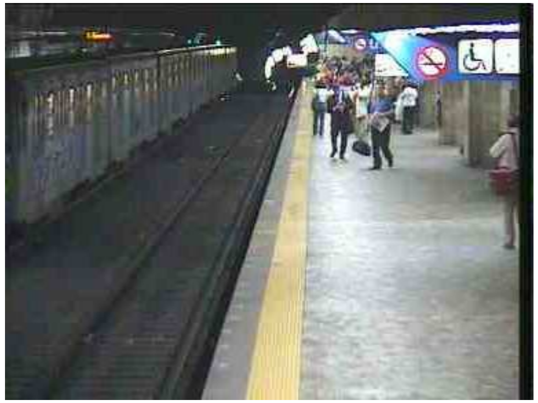
Experimentation [1]

- Video sequences of CARETAKER project

  (http://www.ist-caretaker.org/)

- Cameras are set up in Rome (Italia) subway stations





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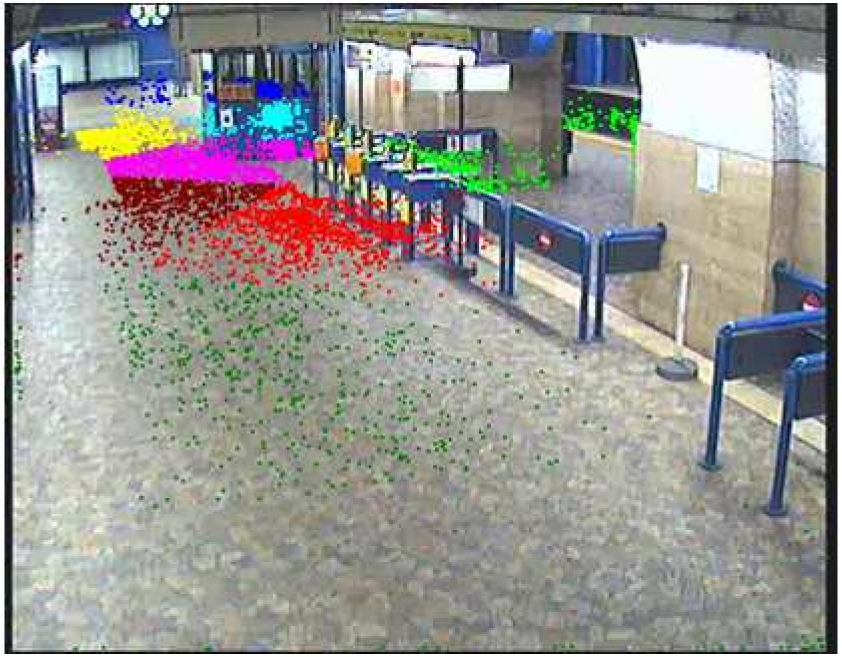
Experimentation [2]



8 learned lost zones

The yellow polygons show the outline of the learned lost zones. The red polygons show the outline of the entry zones, exit zones.

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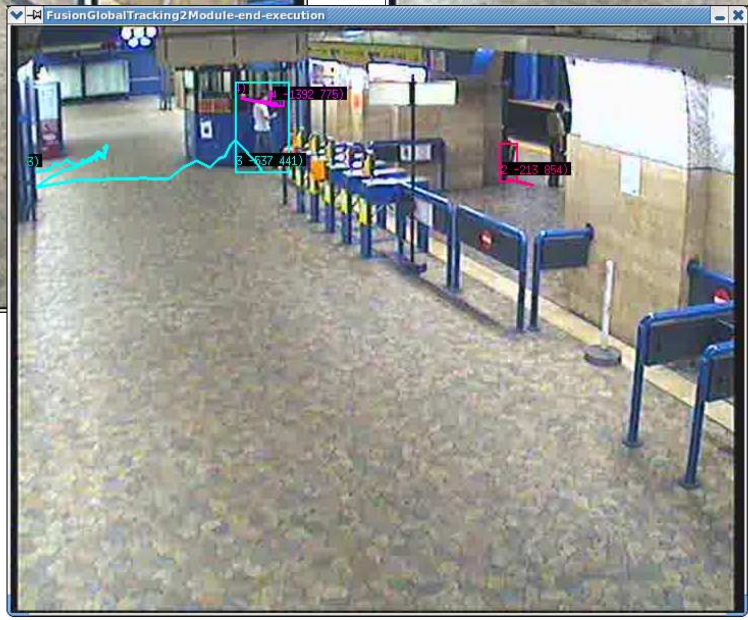
Experimentation [3]

t = 709 s

t = 711s without the algorithm



t = 711s with the algorithm

Experimentation [4]

t = 901 s

t = 903s without the algorithm

t = 903s with the algorithm

Experimentation [5]

Summary of results in two cases: with or without the proposed algorithm

	Without the algorithm		With the algorithm	
	Number	Percentage (%)	Number	Percentage (%)
Complete trajectories	758	9.0	795	9.9
Incomplete trajectories	3086	36.8	2778	34.5
Noise	4550	54.2	4481	55.6
Total	8394	100	8054	100

Conclusion and Future Work [1]

- Present a method in order to repair people trajectories in videos.
- Advantages
  - Require little a priori knowledge by exploiting the structure of the scene.
  - Compute trajectory confidence value to filter out noise and to evaluate the algorithm.
  - Define the notion ‘zone triplet’ => representation of general paths, compatible with complex scenes without clear paths, roads.
  - Good preliminary results

Conclusion and Future Work [2]

- Drawbacks
  - Depend on training videos and tracking quality
    - Need enough complete trajectories
  - Large number of short and incomplete trajectories
  - Can repair wrongly lost trajectories
  - Cannot handle crowded scene (people crossing each other)

Conclusion and Future Work [3]

- Future work
  - Using object appearance model for the repair process
  - The first zone of the zone triplet does not have to be a start zone, but could be anywhere
    - This start zone defined as a first zone was used to limit the space for searching trajectories to be fused and hence limits the repair process choices.

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THANK YOU FOR YOUR ATTENTION

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