Group Tracking and Behavior Recognition in Long Video Surveillance Sequences

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Abstract: This paper makes use of recent advances in group tracking and behavior recognition to process large amounts of video surveillance data from an underground railway station and perform a statistical analysis. The most important advantages of our approach are the robustness to process long videos and the capacity to recognize several and different events at once. This analysis automatically brings forward data about the usage of the station and the various behaviors of groups in different hours of the day. This data would be very hard to obtain without an automatic group tracking and behavior recognition method. We present the results and interpretation of one month of processed data from a video surveillance camera in the Torino subway.

1 INTRODUCTION

Group tracking and event recognition in surveillance and security is an important research area. Dangerous and criminal behaviors are mostly observed within groups of people. This paper presents an approach for group tracking and behavior recognition in a subway station applied to long video surveillance sequences (around 2 hours per video). As stated in (Guo et al., 2010), in recent years, research on action recognition focused on isolated action recognition for short videos and (Guo et al., 2010) recently proposed an approach for arbitrary lengths of videos. Our approach recognizes events in long videos and handles multiple actions at once. The long videos used in (Guo et al., 2010) are not more than 20 minutes long and their approach can recognize multiple actions, however one action after another.

Our technique considers a chain process consisting of 5 consecutive steps as shown in Figure 1 for group tracking and behavior recognition. The steps are: 1) segmentation, 2) blob detection, 3) physical objects tracking, 4) group tracking and 5) event detection, similarily to (Zaidenberg et al., 2012). However our approach combine the technique presented in (Zaidenberg et al., 2012) with a global tracker algorithm (Badie et al., 2012) to improve the results of the group tracking. More specifically, after apply the group tracking algorithm presented in (Zaidenberg et al., 2012) we apply the global tracker algorithm and finally the event recognition technique. In this paper, we focus on the steps 4 and 5. For the previous stages in the processing chain, we use a MoG-based approach for step 1 (Nghiem et al., 2009), a connected region approach for step 2, and an appearance matching approach for step 3 (Chau et al., 2013).

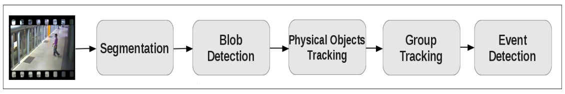

Figure 1: Processing chain for videos.

(Chang et al., 2011) propose a group detection-tracking technique based on paths producing a weighted graph where the edges represent the probability of individuals belonging to a group. On the other hand, they use a probabilistic motion analysis technique for scenario recognition which uses the spatio-temporal pattern. However, the events recognized in (Chang et al., 2011) are very general, *e.g.* group formation, group dispersion, etc. Our work models more complex scenarios: we consider, among others, queues at turnstiles, groups blocking a passage, etc. Ryoo and Aggarwal's (Ryoo and Aggarwal, 2010) technique detects group formation and group activities using a stochastic grammar. Grouping is determined using spatio-temporal relations.

(McKenna et al., 2000) propose a robust approach which tracks people as they form groups using an adaptive background subtraction technique and using color information to handle occlusions. Nevertheless, they do not consider the group as a new entity because

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their technique tracks individuals before and after the group formation. (Zaidenberg et al., 2011) proposed a group tracking approach which first uses a people detector followed by a frame-to-frame tracker (F2F). The output of the F2F tracker is a set of trajectories of the people which is used together with additional features to create groups and then to track them. However, the human detector technique requires the videos to be corrected/calibrated before proceeding to the experiment. On the other hand, our technique does not need any pre-processing of the video.

Vishwakarma and Agrawal in (Vishwakarma and Agrawal, 2012) classify and list the existent event recognition techniques. The classification begins with 2 main categories: non-hierarchical and hierarchical. The non-hierarchical category is divided into two classes: space-time and sequential. Then the space-time category is divided into 3 classes: volume, trajectories and features. For the sequential classification there are 2 subcategories: exemplar and state-based. On the hierarchical branch there are 3 subcategories: statistical, syntactic and description-based. Our approach uses for behavior recognition the framework *ScReK* (Scenario Recognition based on Knowledge) (Zaidenberg et al., 2012), which is under the description-based/hierarchical category. We decided to use *ScReK* for the simplicity of scenario modeling in different application domains.

2 GROUP TRACKING

The social definition of a group is *people that know each other or interact with each other*. McPhail and Wohlstein (McPhail and Wohlstein, 1982) propose *two criteria defining a group: proximity and/or conversation between two or more persons*. It is difficult to automatically detect in a video if the people know each other or their type of interaction. This leads us to use a derived definition on observable properties as in (Zaidenberg et al., 2012) and (Zaidenberg et al., 2011), hence a group is: *two or more people who are spatially and temporally close to each other and have similar direction and speed of movement*, or *people having similar trajectories*.

The group tracking technique presented in this paper is based on the one proposed in (Zaidenberg et al., 2012). The input of our algorithm is a set of trajectories of the physical objects. The approach characterizes a group through three features: the average of the intra-object distance, the average standard deviations of speed and direction. These 3 features are used to define a coherence criterion: $groupIncoherence = \omega_1 \cdot distanceAvg + \omega_2 \cdot speedStdDev + \omega_3 \cdot directionStdDev$, where ω_1,ω_2 and ω_3 are normalization parameters. We actually need to minimize *groupIncoherence* value because with a lower value, the group coherence is higher. In the experimentation the values assigned to these parameters are: ω_1 = 7 and ω_2 = ω_3 = 5 (after using cross validation), benefiting distance over speed and direction similarity which are quite noisy. From this definition, when a group has a low value of the coherence criterion (the *groupIncoherence*), it means that the probability of this entity being a real group is high.

Our group tracking algorithm consists of 4 phases: creation, update, split/merge and termination. For a robust detection of coherent groups, we use people trajectories over a time window, called delay T. This parameter is set to 20 frames for our experimentation. This value was chosen as a trade-off between the need for trajectories to be long enough but without adding a big delay to the system.

To find similar trajectories, we use the Mean-Shift clustering algorithm (Fukunaga and Hostetler, 1975) because it does not require to set as input the number of clusters. However, Mean-Shift does require a *tolerance* parameter determining the size of the neighborhood for creating clusters.

A trajectory is defined as $Traj = \{(x_i,y_i), i = 0 \ldots T-1\} \cup \{(s_{x_i}, s_{y_i}), i = 1 \ldots T-1\}$ where T is the temporal window of analysis (or delay), $(x_i,y_i), i \in [0;T-1]$ in each trajectory is the position of a group in the same frame i, and $(s_{x_i}, s_{y_i}) = speed(i-1,i), i \in [1;T-1]$ is the speed of the group between frames $i-1$ and i. If k positions on the trajectory are missing because of lacking detections, we interpolate the k missing positions between known ones. Each trajectory is a point in a $2(2T-1)$-dimensional space. Mean-Shift is applied on a set of such points.

We set the *tolerance* to 0.1, considering grouping trajectories distant by less than 10% of the maximum. This value is quite low because clustering is used only to group very close people, the case where people temporarily split being handled by the update step described below.

The **creation** step consists in creating a group for each cluster of two or more physical objects (not annotated as NOISE) and not yet being assigned to an existing group. In case of a single physical object labeled as GROUP_OF_PERSONS at frame $t_c - T$, its trajectory is analyzed through the time window , t_c being the current time. If this physical object maintains the size of a group, or is close to other physical objects, then the creation of a group is possible and the algorithm computes its *groupIncoherence*. If the resulting value is low enough, the group is kept.

The **update** step considers the relative evolution of a physical object and a group through the time window (from frame $t_c - T$ to t_c) using the *groupIncoherence* defined above. It adds the physical object under consideration to the group and computes the incoherence of the obtained group through the time window. If the new physical object is really part of the group, the *groupIncoherence* value stays low and the physical object is definitely added to the group.

The **split** step considers a physical object which moved away for a large number of frames from its group. Then, it is highly probable that this physical object is not going to be included into the group during the update step. Therefore, the physical object splits from the group. If a new group is formed from this object and other objects that have split from the same group, then we consider that the old group has split into the new and what remains of the old. The **merge** step considers 2 groups g_1 and g_2 which can be merged if 2 physical objects, one in each group at frame $t_c - T + k$ ($k \in [0; T-1]$), are linked to the same object in frame $t_c - T + l$ ($l \in [k+1; T-1]$). The oldest group between g_1 and g_2 is kept and all the physical objects of the disappearing group are included into the remaining group.

The **termination** step consists in deleting the old groups. A physical object detected at a largely outdated frame (*e.g.* $t_c - 5T$) is erased at frame $t_c - T$ and the empty groups are erased also. This implies that the groups without new physical objects for $5T$ frames are erased.

At the end of the group tracking phase, we obtain an output, which is used as the input of the behavior recognition stage. The output consists of a set of tracked groups (maintaining a consistent id through frames). Each group is associated with 7 features (such as the intra-object distance, the speed or the orientation, among others) and is composed of detected physical objects at each frame.

2.1 Global Tracking

In some cases, the tracking algorithm may have difficulties to keep track of a group. For example, it happens when a group leaves the scene and re-enters or when an element of the scene occludes the group for a significant time. In this case, the tracking algorithm considers that the two groups are different and labels them with a different ID. In order to solve this problem, we use a method called re-acquisition that tries to connect the current IDs with the previously lost IDs in a predefined time window, based on the appearance of each group. This step can be considered as an extension of the tracking algorithm at a larger scale.

The first step of the re-acquisition method is to extract relevant data from each group to compute a visual signature. To compute this visual signature, a descriptor based on covariance matrices is used (Bak et al., 2011). This descriptor has shown very good results in the case of multi-camera re-indentication of people. The second step is to arrange the groups into several clusters depending on the distance between their visual signature. The groups belonging to the same cluster are then considered as the same group because their visual signature is nearly identical.

The main advantage of the re-acquisition method is to reduce the tracking errors due to occlusions by merging the IDs of groups representing the same group of people.

3 BEHAVIOR RECOGNITION

The behavior recognition stage used in the present approach is the one proposed in (Zaidenberg et al., 2012) named *ScReK*. (Zaidenberg et al., 2012) identify 2 phases in a behavior recognition process: *the application knowledge (what are the expected objects? what are the event models?) and the event recognition algorithm*. They consider that knowledge should be modeled by vision experts (specialists in vision algorithms) together with and application domain experts (specialists in the expected events of their domain).

The knowledge is modeled through the ontology shown in Figure 4 and the grammar proposed in (Zaidenberg et al., 2012). The ontology is implemented with the *ScReK* declarative language. The grammar describes the objects and events using the extended BNF (Backus Naur Form) representation. The objects are defined using an inheritance mechanism: the object O_i inherits all the attributes of its parent O_j. The attributes are defined based on 11 basic types: *boolean*, *integer*, *double*, *timestamp*, *time interval*, *2D point* (integer and double), *3D point* (integer and double), and *list of 3D points*.

On the other hand, with *ScReK* we also represent the knowledge of the event models. They consist of 6 parts: (1) Type of the scenario (4 values are possible: *PrimitiveState*, *CompositeState*, *PrimitiveEvent*, *CompositeEvent*). (2) Name of the event model. (3) List of physical objects involved in the event. (4) List of sub-events composing the event model. (5) List of constraints for the physical objects or the components (6) Alarm level giving the importance of the scenario model (3 values are possible: `NOTURGENT`, `URGENT`, `VERYURGENT`). This is illustrated with the example presented in Figure 3.

The behavior recognition algorithm deals with spatio-temporal constraints on the detected groups. The algorithm uses optimal event models due to the restrictions of: maximum two components and one temporal constraint (Allen's algebra) between these components. Using this optimization, the algorithm generates an event model tree. The tree defines which sub-event (component) triggers the recognition of which event: the sub-event which happens last in time triggers the recognition of the global event. For instance, if the event A has two components B and C with constraint: before C, then the recognition of C triggers the recognition of A. The tree triggers the recognition of the only events that can happen, decreasing the computation time.

4 EXPERIMENTS

The experiments of our research are oriented on demonstrating the robustness of our approach and due to the large amount of data that we have processed, it was possible to generate statistics. In fact, we have applied the process chain (see Figure 1) on the dataset recorded in January 2011 for an European project in the Torino subway, on the camera named *Tornelli*. Recordings contain 1 month of data and were done from 2010/12/30 to 2011/02/03, from 7 to 11am and 4 to 10pm. We have processed 241 video chunks of 2 hours, that is to say 482 hours of video. We focus on analyzing the results obtained in the group tracking and event recognition stages.

The behavior recognition process needs the model of the group events that we want to recognize in the scene *Tornelli*. Several of these events use the definition of predefined contextual zones in this scene, as shown in Figure 2.

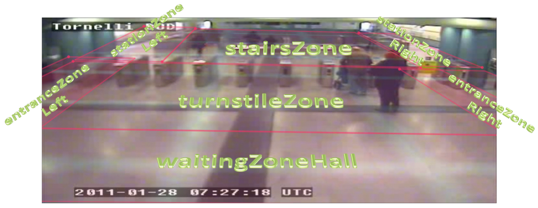


Figure 2: Contextual zones of the Tornelli view.

Based on the defined zones, we have modeled scenarios, representing interesting trajectories of subway users. For instance, the scenario *Group_Hesitating_Hall* represents groups going first to the turnstiles and then returning to the hall instead of going through the turnstiles. It appears that most of the time, when someone does not have a valid ticket then needs to come back to use the vending machines across the hall and after the group goes through the turnstiles. This scenario is expressed as follows, in Figure 3:

```
CompositeEvent(Group_Hesitating_Hall,
    PhysicalObjects((g : Group), (z1 : Zone),
                                 (z2 : Zone))
   Components((c1 : CompositeEvent
        Group_Changes_Zone(g, z1, z2))
               (c2 : CompositeState
        Group_Stays_Inside_Zone(g, z2)))
   Constraints((z1->Name = turnstileZone)
                (z2->Name = waitingZoneHall)
                (c1 meet c2) )
    Alarm ((Level : NOTURGENT))
)
```

Figure 3: Example of the model event: Group Hesitating Hall.

Considering the above, we obtain the ontology for the *Tornelli* view. In Figure 4 we show an extract of the ontology obtained.

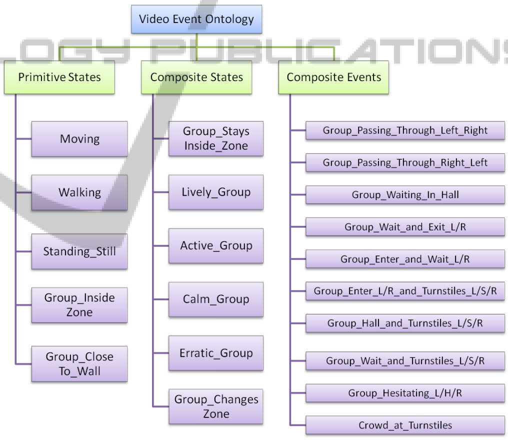


Figure 4: Extract of the proposed group event ontology for the Tornelli view.

Using our approach in the dataset mentioned above, together with the ontology shown in Figure 2, it was possible for us to recognize multiple behaviors at once in each processed video.

4.1 Results and Interpretation

The number of accumulated groups over the recording period per hour is shown in Figure 5: the first result of this study is to confirm that the peak hours are indeed 7-8 am and 5-6 pm. It can also be noticed that people tend to travel in groups rather in the afternoon than in the morning. Indeed, people traveling in the morning are mostly people going to work, when afternoon travelers are more likely to be tourists or people traveling for leisure. This tendency is confirmed by the generally higher number of groups observed in the afternoon compared to the morning. Figure 5 also plots the difference in the number of groups on weekends (Saturdays and Sundays) and on weekdays (from Mondays to Fridays). The result, as expected, confirms that the number of groups is lower on weekend mornings and heigher on weekend evenings than during the week.

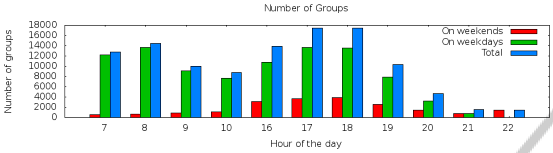


Figure 5: Number of detected groups per hour of the day and difference between weekends and weekdays.

We have measured which activities are the most frequent depending on the hour of the day. In the next graphs (Figures 6 to 12), the x axis represents the hour of the day and the y axis, the percentage of occurrences of the given activity within all activities detected in the given hour (listed in Figure 4). We count as an occurrence the detection of a group performing an activity (at a given hour). The same group can perform several activities at the same time or at different times. For instance, a group can be detected as "Walking" and "Erratic_Group" because "Walking" refers to the speed, whereas "Erratic_Group" refers to the trajectory. Similarily, the same group can be "Walking" at a point in time and "Standing_Still" at another.

Figure 6 compares 3 categories of speed of movement and 3 agitation levels of groups. This comparison shows first that the speed of groups does not depend much on the time of day. The most represented category is "Standing_Still" where the speed (s) is the lowest ($s < threshold_1$). The next most frequent category is "Walking" (which also includes running since all speed above a threshold is included in it: $s \geqslant threshold_2$). Finally comes the middle category "Moving" corresponding to slow motion ($threshold_1 \leqslant s < threshold_2$). The values for $threshold_1$ and $threshold_2$ are defined considering the interval $[minimum, maximum]$ for people speed in this type of videos, the interval is divided in 3 equivalents parts. This is the moment to remind that the same group can perform several activities. When groups go through the turnstiles, they almost always stop for a few seconds. An individual going through the turnstiles has, most of the time, to significantly slow down or stop for a short time. In a group, all the members have to go through for the group to move on. Hence the stopping time is increased in the case of a group. The high frequency of the "Standing_Still" activity is explained by the turnstiles visible in this view.

The agitation level is represented by the variation of the size of the bounding box of a group. We consider 3 categories from *no agitation* ("Calm_Group", having a bounding box with very stable size) to *little agitation* ("Active_Group") to *high agitation* ("Lively_Group", the bounding box's size varies a lot, meaning that group members move around more). Figure 6 shows that most of the time, this middle category predominates. Groups are neither too calm, nor too agitated. Moreover, it is more common for a group to be lively rather than calm.

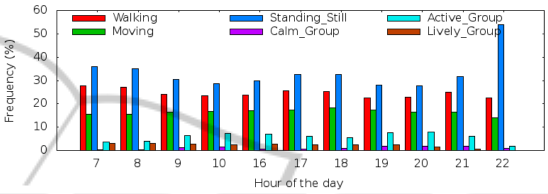


Figure 6: Comparison of speed of groups and variation of group's bounding boxes during the day.

Figure 7 presents the distribution of the activities "Erratic_Group" and "Crowd_at_Turnstiles" over the hours of the day. Unlike the previous graph (Figure 6), this graphs' y axis represents the percentage of occurrences of each activity in the given hour in relation to other hours (not other activities in the same hour as it is the case previously). This Figure shows that trajectories tend to be more erratic, that is to say less straight, at peak hours. In fact, when more people are present, it is harder to keep a straight trajectory. The "Crowd_at_Turnstiles" scenario represents very wide groups staying in the turnstile zone for longer than 10 seconds. This occurs when the station is crowded and the algorithm fails to detect the small group structures and detects the whole crowd as one group. Although this scenario approximately confirms the afternoon peak hours (5-6 pm), the morning peak hours (7-8 am) are not well distinguished. Nevertheless, the algorithm seems to be working as expected because in the evening there are definitely less crowds. This leads to the conclusion that this particular scenario occurs even outside of peak hours and is not representative of peak hours. Figure 8 presents an example of a little crowd forming at the turnstiles during peak hours. Indeed, as shows this example, the width of a group is not enough to define a crowd and to be more precise, we would need to estimate the density of people inside this group.

Figure 9 shows the frequencies of the activity "Group_Stays_Inside_Zone" in various zones of the scene (as shown Figure 2). This scenario is detected when a group stays inside a zone for more than 10 seconds, not moving. One can notice that groups stay the most in the turnstile zone, which is consistent with

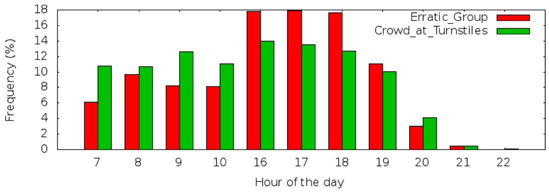
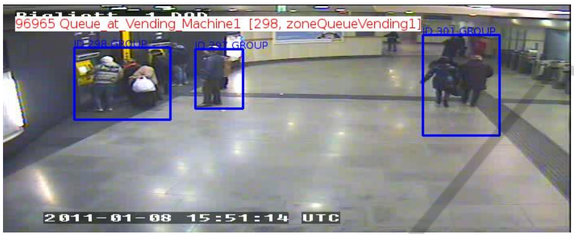


Figure 7: Distribution of the “Erratic_Group” and “Crowd_at_Turnstiles” activities over the hours of the day.



96965 Queue_at_Vending_Machine1 [298, zoneQueueVending1]

Figure 8: Example of queue at vending machine.

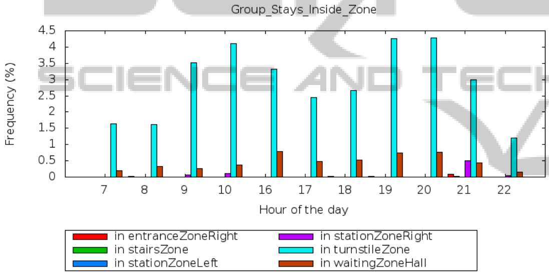


Figure 9: Comparison of stagnancy zones.

the conclusion of Figure 6 (groups have to stop at the turnstiles). The other significant zone of stagnancy is the waiting hall, where people meet, wait for each other, wait for someone to buy tickets, or just stay to chat. Once inside the station, people mostly go straight to the trains.

Figure 10 compares several typical trajectories that groups take in the station. The most frequent activity is entitled “Group_Hesitating_Hall” and is defined as a group first detected in the turnstile zone then transitioned to the waiting hall zone. We call this *hesitating* because the group has not decided to enter the station yet. In most cases, someone is needed to buy a ticket. This activity occurs more frequently in the afternoon than in the morning. This can be explained, as already mentioned, by the fact that morning travelers are mostly people going to work, hence they know the way, have their ticket, and go straight to their train without hesitating. Afternoon users are more frequently unusual users, hence more prone to hesitating. The similar activities “Group_Hesitating_Left” and “Group_Hesitating_Right” represent groups that went from the turnstile zone to the left or right entrance zone. The first four scenarios in Figure 10 describe various typical trajectories: entering from the left or the right, going through the turnstiles and to the left or right side of the station.

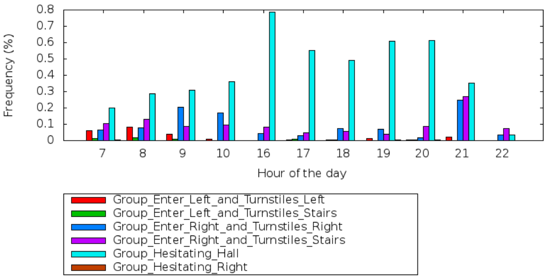
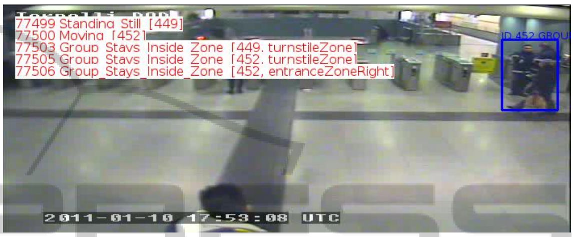


Figure 10: Comparison of frequent behaviors.



77499 Standing_Still [449]
77500 Moving [452]
77503 Group_Stays_Inside_Zone [449, turnstileZone]
77505 Group_Stays_Inside_Zone [452, turnstileZone]
77506 Group_Stays_Inside_Zone [452, entranceZoneRight]

Figure 11: Illustration of a stagnant group: in the right entrance zone a group of subway security staff is stagnant.

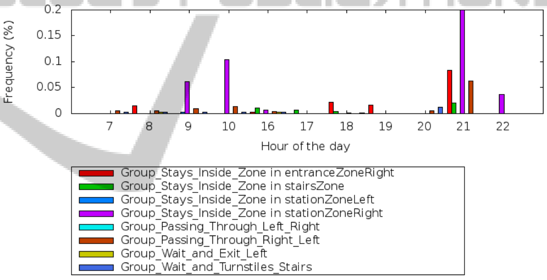


Figure 12: Comparison of rare behaviors.

We can observe that here again, activities on the right side of the station are better represented than on the left side. This is most likely due to the harder detection in the left side of the image.

Figure 11 shows an example of occurrence of the events “Group_Stays_Inside_Zone in entranceZoneRight”, where the stagnant group is actually a subway security team.

Figure 12 first focuses on the other zones where stagnancy was detected that do not appear clearly on Figure 9. In figure 12, we can see that groups sometimes stay on the right zone of the station, but never on the left (in fact, there is only 1 occurrence of “Group_Stays_Inside_Zone in stationZoneLeft”). Similarily, groups sometimes stay in the right entrance of the station, but never in the left. This phenomenon can be explained by the quality of the image. In fact, the camera lens is a little blurry on the left side, which might explain low detection quality. Nevertheless, Figure 12 shows that stagnancy in those unusual zones mostly occurs outside of peak hours. During peak hours, there are too many people for a group to comfortably stagnate in one of those transit zones.

Figure 12 also shows other trajectories taken by groups but the occurrence rate of these trajectories is lower than those in Figure 10. We have detected a few groups passing through the station without entering the turnstiles (17 occurrences of "Group_Passing_Through_Left_Right" and 1 of "Group_Passing_Through_Right_Left"), 2 occurrences of groups waiting in the hall and then leaving the station. Finally, we have detected 8 occurrences of groups waiting in the hall before entering the station and taking the stairs. The rarity of these detections might be explained by the difficulty to detect such events, especially during peak hours.

5 CONCLUSIONS

We have presented an approach for group tracking and behavior recognition. Our approach works in real time and in long surveillance videos (1 month per view). In the experiment section, we have shown that our method is capable of recognizing multiple and different events at the same time. This demonstrates the robustness of our approach to processing videos regardless of their length. Thanks to the simplicity of using the event recognition language (*ScReK*), it was possible to model complex scenarios for the *Tornelli* scene as shown in Figure 8.

On the other hand, the amount of videos processed allows us to analyze the results, obtaining the different comparisons presented in the graphs of the previous section.

We consider for future work the addition of probabilities to the event recognition phase, which could help to predict dangerous and criminal events. The results obtained here show us a big challenge for prediction of such events because there are not many examples with this kind of behaviors.

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