Improving public transportation management and planning using Closed Circuit TeleVision cameras analysis

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CARETAKER IST-4-0227231

Content Analysis and Retrieval technologies to Apply Knowledge Extraction to massive Recording
✓ **Introduction**

✓ **Video analysis tools proposed**
  - People detection (IDIAP)
  - Platform occupancy by metros (MULT/ACIC)

✓ **Algorithms evaluation and results exploitation**
  - People detection evaluation
  - Platform occupancy evaluation
  - Joint analysis and end-user feedbacks

✓ **Conclusion & future work**
Today’s **Video Content Analysis (VCA)** enables:

- **reliable extraction of surveillance-like scenarios or events**
  (tracking, activity recognition, abandoned luggage detection, . . .)

However CCTV video streams represent a **useful source of information in urban planning and resource optimization applications**.

**Pros:**
- Provide “above physical detection” information
- **Wide-area measurements** (replace/complement conv. physical detectors).
- Performance can be **verified** and detectors **easily reconfigured**.

**Interests:**
- **Statistics gathering** and **“long-term” analysis** of data
  - Provide interesting insights regarding station usage (person counting, infrastructure occupation and usage…)
  - Allow to identify **operation general trends** (metros distribution…).
Video analysis tools proposed

- People detection (IDIAP)
  - Estimate number of people in one camera view (turnstiles view)

- Platform occupancy by metros (MULT/ACIC)
  - Estimate the time/frequency the metros stay in stations (platform view)
People detection (IDIAP)

- Estimate number of people in one camera view (turnstiles view)

**Approach: machine learning algorithm**

- Detection algorithm: image scanning
  - for all possible subwindows of an image
    - apply human vs non-human classifier
  - cluster windows with human detection

- Proposed approach: cascade of weak classifiers
Boosting learning

- LogitBoost classifier: combines output of ‘weak classifiers’
- Weak classifiers: based on measures computed on subwindows of test window
- Learning process: automatically select the best weak classifiers (and their number)
Weak classifiers based on features computed over one subwindow

- at each pixel: extract a pixel feature vector $H$ (8 dim.)
- Features: 
  - Intensity: contains shape information
  - Foreground: shape + help to quickly discard bad window candidates

Compute **covariance** of pixel features
- **8x8 matrix**: involve costly matrix operations used for classification
- Use covariance between feature subsets (of dimension 2, 3 or 4)
Training data:
CARETAKER data from Torino and Rome, PETs, CAVIAR, UBS

✓ Positive examples (hand labeled):
  ➢ around 10 000
✓ Negative examples:
  ➢ Sampled regions from natural images with inconsistent foreground maps
  ➢ Bootstrapping

Results
➢ Good results! Equal error rate around 90%
➢ Use of subset: similar accuracy, but 15 times faster
✓ Platform occupancy by metros (MULT/ACIC)
  ➢ Estimate the time/frequency the metros stay in stations (platform view)
✓ **Approach:** tracking-based algorithm
   - No background modeling estimation (more robust).
   - Main idea:
     - use trajectories from randomly distributed particles in image to perform train arrival/departure detection.

✓ **Principle:**
   - quickly locate moving objects and determine whether their motions are compatible with requirements of train arrival/departure (location, direction, speed . . . ).
   - Particles are randomly initialized in a region of interest (“rails zone”),
   - Tracking is activated for each particle when defined criterion is met (~ motion detected).
   - Relevant trajectories are filtered and eventually used to derive the final detection.
✓ **Particle distribution:**

Inactive particles are randomly distributed for each new image with a non-uniform rule using the calibration information, to take into account perspective over the region of interest (detection area).
Particle activation:
- Activation criterion based on an instantaneous motion detection (thresholded frame-differencing operator).

Particle tracking:
- Particles continuously track the motion of the underlying object using a block-matching algorithm.

Filtering of trajectories:
- Trajectories are analyzed by computing a set of various features; linearity of track, track length, track duration, track direction, start/stop particle location, and classified as relevant ones and uninteresting ones.

- Typically, trains/metros are characterized by linear trajectories, mean direction parallel to the rails, speed linearly increasing/decreasing.
- On the other hands, passengers and tracking errors are most likely to have much more chaotic trajectories.
✓ **Train arrival/departure detection:**
   - Remaining trajectories are scored;
     - low values are attributed to trajectories of weak interest,
     - while high scores are given to highly relevant ones.
   - Total score is compared to a threshold to decide whether a train is potentially arriving/departing;
     - arrival/departure time are lastly estimated using a Finite State Machine (FSM), which allow to distinguish between arrival and departure, and to compute the resulting platform time-occupancy.
Outlines

- Introduction

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- Algorithms evaluation and results exploitation
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- Conclusion & perspectives
Experiment with Rome underground data
- 14 consecutive mornings, from 6h00 to 11h30 AM

People detection (IDIAP)
- Camera near turnstiles and train exit
  - People going through turnstiles
  - People coming out the train
  - People inquiring at front desk
  - People at the ticket vending machine
- Count people every 5s, average on 3 min

Platform occupancy by metros (MULT/ACIC)
- Estimate the time/frequency the metros stay in stations (platform view)
- Process every frame, data annotation (GT)
- **Large temporal variability**
  - Different flows of people
    - Large number of people at train arrivals, otherwise can be empty
  - People stay a short time in camera view
  - Average amount of people detected (over 3 minutes) between 0 and 13
Evaluation

- Composite sequence from different videos
- Robust and accurate
- Under-estimate the right number of people when crowding (occlusions...)

Example over one morning (Wed)

- Activity begins really at 8h
- Peak at 9h
- Decrease around 11h30
- Red curves: mean (blue curve) +/- 2 standard deviation
- Saturday: High activity and variations (very different from week days)
- Sunday: calm (also different from week days)
People detection evaluation (4)

- Wednesday, Friday, Thursday
  - Follow week average
  - Unusual events visible

Lost japanese tourists
Large variability in platform occupancy

- Distribution of train platform occupancy (computed on all sequences)
  - Average value 45s, but kind of Gamma distribution
  - Outlying values: far below (10s) or above (up to 3 min, even 6 min).

Outliers mostly due to regulation purposes, safety checks, incidents on platform, signal failures or break-down of systems.

Histogram of platform time-occupancy.
Platform occupancy quantitative evaluation (2)

Detection results for the whole sequences

- **Average detection rate:** 96.59% (710/735)

<table>
<thead>
<tr>
<th>Day</th>
<th>2007.06.02 (Sat)</th>
<th>2007.06.03 (Sun)</th>
<th>2007.06.04 (Mon)</th>
<th>2007.06.05 (Tue)</th>
<th>2007.06.06 (Wed)</th>
<th>2007.06.07 (Thu)</th>
<th>2007.06.08 (Fri)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Detection rate (nb)</td>
<td>100% (35/35)</td>
<td>97.36% (37/38)</td>
<td>98.38% (61/62)</td>
<td>96.77% (60/62)</td>
<td>94.44% (51/54)</td>
<td>100% (62/62)</td>
<td>92.59% (54/54)</td>
</tr>
<tr>
<td>Detection rate (time)</td>
<td>100%</td>
<td>95.90%</td>
<td>98.20%</td>
<td>97.89%</td>
<td>97.05%</td>
<td>100%</td>
<td>91.61%</td>
</tr>
<tr>
<td>Average stop duration (std)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- detection -</td>
<td>37.14 (10.53)</td>
<td>42.77 (35.73)</td>
<td>44.41 (16.86)</td>
<td>53.98 (52.92)</td>
<td>46.63 (15.87)</td>
<td>45.70 (29.74)</td>
<td>45.33 (22.58)</td>
</tr>
<tr>
<td>- ground truth -</td>
<td>37.21 (10.45)</td>
<td>43.21 (35.40)</td>
<td>44.34 (16.84)</td>
<td>53.22 (52.21)</td>
<td>46.08 (15.98)</td>
<td>45.99 (29.66)</td>
<td>45.38 (22.53)</td>
</tr>
<tr>
<td>Mean arrival delay (s)</td>
<td>0.77</td>
<td>0.63</td>
<td>0.58</td>
<td>0.83</td>
<td>0.63</td>
<td>0.78</td>
<td>0.62</td>
</tr>
<tr>
<td>Mean departure delay (s)</td>
<td>0.69</td>
<td>0.84</td>
<td>0.72</td>
<td>0.97</td>
<td>0.77</td>
<td>0.48</td>
<td>1.05</td>
</tr>
</tbody>
</table>

- **General trends:** Sat/Sun seems to have less metros and shorter stops!
No clear trends in the metros frequency or platform occupancy...
Cumulative plots of platform occupation by metros (reflect both train stop duration and frequency)

Week-days (Mon-Fri)

Week-end days (Sat-Sun)

Saturdays/Sundays have significant lower platform occupation than week-days!
More people on Saturdays.
Fewer and shorter trains on Saturdays.

Statistics are coherent independently, but…
Joint analysis and end-user feedbacks (2)

- Counting plots with **filtering out instants where train is present** (count replaced by average of “no-train” count)
  - Filters out peaks due to people coming out from the train.
  - Characterizes usual activities in turnstiles view, excluding the arrivals.

- Still high variability in people counting
  Activity in the camera view very irregular

- Metro traffic on Saturdays does not influence counting!
Joint analysis and end-user feedbacks (3)

Average number of people per morning on train presence time (blue) vs on train absence (green).

- Average difference between the 2 curves

  Clearly larger difference on week days (3.1 in average) than on week-ends (1.5 in average)

Exhibits a different behavior of passengers on week-ends (people takes different routes and flows e.g. “tourists” vs “weekly workers”)

![Graph showing average number of people per day with blue line for train in station and green line for no train, with peaks and troughs indicating differences in attendance on weekdays vs weekends.](image)
End-users confirm that normal/expected operational behaviors correspond to platform occupancy measures…

- Station is supposed to be more crowded during week-days.

Why opposite counting results?

- Turnstiles view is NOT representative of the platform (and whole station) activities.

Roma cameras connected to platform area.
Joint analysis and end-user feedbacks (5)

- Understanding (week-days) peaks of activities:
  - People counting average
    - 7.2 persons in the turnstiles view when a train is present
    - only 4.5 persons otherwise.
Conclusion & future work

Conclusion

✓ Demonstrate interest/robustness of proposed tools
  ➢ People detection evaluation
  ➢ Platform occupancy evaluation

✓ Main contributions
  ➢ Use of a video analysis tools for statistics gathering
    ▪ People detection & platform occupancy
    ▪ Demonstrate interest of results analysis for infrastructure monitoring
      ▪ Identification of unusual activities (tourists losts, outliers…)
      ▪ Identification of pattern of activities in station usage (WE vs week-days)

✓ Future work
  ➢ Process other cameras connected to the platform to confirm the behaviors observed in the « turnstiles view » during WE
  ➢ Process video streams from other stations (e.g. to understand the domino effect of potential delays, compare station occupation/usage
Thank you!

Questions?

For further information about CARETAKER project (FP6-0272312), please visit

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