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Real-time Pedestrian Surveillance with Top View Cumulative Grids

Abstract This manuscript presents an efficient approach to map pedestrian surveillance footage to an aerial view for global assessment of features. The analysis of the footages relies on low level computer vision and enable real-time surveillance. While we neglect object tracking, we introduce cumulative grids on top view scene flow visualization to highlight situations of interest in the footage. Our approach is tested on multiview footage both from RGB cameras and, for the first time in the field, on RGB-D-sensors.

1 Introduction

The security of public areas is a critical part for pluralistic society. While we enjoy the freedom to use public facilities ranging from bus stations to airports for personal purposes, we have to be aware that these places are also the most likely areas for an impending attack with a high death toll. Apart from terroristic attacks, burglary and beggary are also most likely occur there, because these places bear with a great amount of anonymity for the subjects using them. Therefore, authorities strive to increase security with public surveillance (CCTV). Apart from the psychological factor, the camera system also directly helps avoiding crimes by live streams which help monitoring officers to alert ambulance. Further, recorded footage might later help convict suspects once the charges have been pressed by victims. Human operation to CCTV monitoring however introduces the risks that crucial events are missed due to attention shifts or blind spots in the surveillance area. Furthermore, when the video footage is juxtaposed on monitors, it becomes a non-trivial task for the monitoring officer to build a mental map from the image streams. A subject leaving the imaged area in one window might not appear afterwards in neighboring windows. To tackle this problem, several high-level computer vision algorithms have been proposed, to recognise, label and track subjects image by CCTV. However, a failure of such a system to detect a single subject once can become fatal, if that subject turns out to be the villain, or a terrorist. In this paper we want to overcome the weaknesses of both the juxtaposition of image streams for human-based monitoring and the high-level vision based automatic tracking. We propose to build the mental map virtually by rendering a top view from one to many input cameras. The evaluation of the depicted motion is left to the human monitoring officer but our algorithm visualizes occupancy times and the scene flow on the top view to help with the judgement of a given situation. For the first time, we present an approach that incorporates traditional RGB camera based scene surveillance and depth-value based scene surveillances, e.g. from RGB-D sensors or Time-Of-Flight cameras. This enables new hardware setups for public areas, based on depth-sensors that have increasingly gotten affordable over the last three years and that help surveying scenes with varying lighting conditions.

The paper is structured as follows: after briefly revising the state of the art in Sect. 2, we will present an approach to retarget pedestrian surveillance footage into the topview in order to perform motion and video analysis to it, Sect. 3. Two algorithms, one for RGB-data and one for depth data will described in detail. The motion analysis consists of cumulative maps to help crowding detection and the application of optical flows.
In Sect. 4, we will apply the algorithm to an RGB outdoor dataset consisting of eight calibrated cameras and two indoor datasets, before we conclude in Sect. 5. One dataset is a depth-based dataset consisting of one ToF-camera, the other is the surveillance of a train station with for extrinsically calibrated RGB cameras.

2 Related Work

Reprojection and summarization

Image reprojection aims to warp an input image into an arbitrary viewpoint and a typical implementation using an energy functional minimization is formulated by Setlur et al. [41]. Carroll et al. [8] reprojects images in order to artistically introduce a new perspective to a given image, while Sacht et al. [39] reprojects photographic images into specific cylindrical views. The term summarization was coined by Daniel and Chen [11] to reproject an image sequence meaningfully into one single image and was later refined by Botchen et al. [6]. Based on this approach it was shown [9] that ordinary users can learn to detect and recognize visual signatures of events from video visualization. Wang et al. [46] proposed to reproject videos into a 3D environment model for scene awareness. Legg et al. used homographic projection for 3D reconstruction from a single viewpoint [25] and Parry et al. applied this approach to image sequences in sports [33]. Remero et al. [37] summarized activities captured by an aerial camera in natural settings. Further information can be found in a comprehensive survey on video-based graphics and video visualization conducted by Borgo et al. [5].

Pedestrian Surveillance

Classically computer vision strives to detect pedestrians in input footage rather than reproducing them meaningfully. For example Bayesian classifiers [49] to evaluate the presence of an object are widely employed for detecting pedestrians [12, 13]. Multi-person tracking has been implemented differently: the authors of [42] track pedestrians by flow optimization on the ground plane. The authors expand the algorithm with global appearance rules. The method proposed in [3] labels pedestrians the problem by estimating both discrete data and continuous trajectories using global costs. This method relies solely on trajectories and does not involve appearance of Generally, association between data can be performed over a list of frames [34], e.g. in a hierarchical manner. In [22] the authors use tracklets from lower levels in the pyramid and associate them accordingly at a higher level to reduce the computational load. This method introduced in [22] is hierarchical, for example, and uses existing low-level tracklets. In [17], the tracks of pedestrians are refined with motion models. Multi-view methods have been introduced to overcome occlusion introduced in crowding scenarios. Currently, some multi-view based papers [47, 32] learn context models. Crowd density estimations can be used [38] to improve human detection and tracking. The authors of [32] propose an adaptation scheme in which classifiers are learned incrementally through online boosting, so that they adapt to the changes over time. In [44], the authors propose to match a bipartite graph.

RGB-D Imaging

Shotton et al. [43] introduced the Kinect and its underlying algorithm as a tool to capture the human pose from monocular depth images and paved the road for consumer-grade motion capturing with the device. In the wake of the commercial success monocular motion capturing has become the focus of the research community [16, 36, 30]. Mainly, the Microsoft Kinect was used capture datasets and benchmarks. Besides the tracking of limbs and joints quickly other research fields in monocular depth processing have emerged.

One research direction for example was to use the Microsoft Kinect as a hand-tracking device [31]. Frati et al. [15] assume the hand to always be closest limb to the camera while Reheja and his colleagues detect the palm with a circular filter the depth image [35]. Van den Bergh et al. [45] estimate the orientation of the hand from the orientation of the forearm in the depth image. Zollhofer et al. [50] fitted deformable facial meshes to depth data captured from human faces by relying on feature points (eyes, nose) in the depth data. Leyvand et al. also examine the face recognition of identical twins given depth and motion data from the Microsoft Kinect [26].

In 2011, Berger and his colleagues showed that it is also possible to employ multiple depth sensors in one scene for motion capturing research [4]. Using an external hardware shutter [40] they were able to reduce the sensor noise introduced from neighboring Kinects. A similar approach has been introduced by Maimone and Fuchs [28]: each Kinect sensor shakes around its up vector introducing scene motion. This approach was refined by Butler et al. [7] who introduce arbitrary motion to the sensor which has to hang in an acrylic frame and has to be held by rubber bands.

Beside the Kinect sensor, depth imaging is usually conducted by passive stereo or with Time of Flight imaging. Most methods use the range imaging data to initialize stereo matching and impose constraints on the search range depending on the range imaging and stereo noise model. Local methods [24, 18, 20, 10, 48, 29] combine the stereo and the range imaging data term on a per pixel level. Kühnert et al. and Hahne et al. [24, 20] compute confidences in the depth image and let stereo refine the result in regions with low confidence. Nair et al. [29] and Dal Mutto et al. [10] combine confidences from both stereo and the depth image into a stereo matching framework. Global methods such as [14, 19, 23, 29] use spatial regularization techniques in order to propagate more information to regions with low stereo or depth image confidence. Among the global methods, Fischer et al. [14] apply an extension of half global matching [21] to additionally handle depth data. Hahne et al. [19] applied a graph cut approach with a discrete number of disparities.
to sensor fusion. Kim et al. [23] and Nair et. al [29] formulate the fusion problem in as a energy functional that is then minimized. Nair et al.[29] employ adaptive first and second order total variation (TV) with L1 regularization, normally used to estimate optical flow.

3 Proposed Algorithm and Test Datasets

In this section we describe the algorithm for top view summarization maps in detail. Its key idea is outlined in Fig. 2. For each input view $v \in V_{in}$ the algorithm, Alg. 1, requires a background image $I_{v,bg}$ and two consecutive images $I_{v,t}, I_{v,t-1}$. A background image can either be manually set by the user ($I_{v,bg} = I_{v,t_{span}}$) or acquired as mean intensity image over a time span $T$ ($I_{v,bg} = \sum_{t} I_{v,t}$). In order to reproject pixel areas comprised by pedestrians into a topview with a calibrated Homography $W_v : v \in V_{in} \rightarrow v_{topview} \in V_{target}$ the algorithm searches for regions near edges that move parallel to the mean direction of motion for each pedestrian. This can be reasoned by the fact, that in a head-and-shoulder view, i.e. a top view $v_{topview} \in V_{target}$, only head, shoulders and feet are visible and these body parts mainly contribute to edges $e_{ij} \in I_{edge,v,t}$ in an edge image $I_{edge,v,t}$ that are parallel to the mean direction of motion $v_{pedestrian}$ of a pedestrian in a corresponding flow image $I_{flow,v,t}$, while most other body parts appear perpendicular. Thus, the algorithm computes the edge image $I_{edge,v,t}$ of the latest frame and, using the previous frame, it computes the mean flow vector $v_{mean}$ for each pedestrian, i.e. each connected component $CC_{v,t}$ using the optical flow evaluation $I_{flow,v,t}$. This is done by calling Alg. 2. The computation of connected components is performed using the background image $I_{v,bg}$ and a significant colour distance. After having retrieved the mean optical flow vector for each connected component, which is equal to the mean direction of motion for each pedestrian in the image, Alg. 1 calls Alg. 3, which thresholds each edge segment for its collinearity to the mean flow of each object respectively. The threshold is performed by computing the angular difference between the flow vector and the normal to the gradient at each edge pixel and thresholding for the angular difference. Pixel regions in between the remaining edge pixels are filled in a line-sweep manner to arrive at a subset of the connected component pixels. Using the camera calibration, Alg. 1 retargets the remaining pixels into the top view.

In order to make the algorithm applicable for depth-sensor data as well a few alterations are necessary. First, the edge detection is performed on a single channel image and the contrast is at contact borders (e.g., when a foot is rested on the ground), Fig. 4. Second, the re-projection $W_v : v \in V_{in,depth} \rightarrow v_{topview} \in V_{target}$ to the topview can be implemented by exploiting the camera calibration and the depth values, which avoids distortion errors as described in the previous case. Thus, Alg. 4 is implemented to search for edges in the depth maps.
Table 1 Analysis and summarization of a pedestrian database [2]. The crowding that is noticeable at time frames \( t + 2 \), \( t + 3 \), \( t + 4 \) in the input images (first row) can be directly read from the cumulative top view scatterplot (third row). An optical flow computation can be applied to the top view, e.g. to discriminate pixel movements or search for unusual motion patterns.

| \( t \) | \( t + 1 \) | \( t + 2 \) | \( t + 3 \) | \( t + 4 \) | \( t + 5 \) | \( t + 6 \) | \( t + 7 \) |
|---|---|---|---|---|---|---|---|

![Image](image1.png)

Fig. 3 Input footage from a calibrated Time-Of-Flight Sensor (intensity, left, depth value, middle) and a topview of the indoor scene captured by it (right).

Algorithm 1 Image-based Top View Transformation

**Require:** Homography \( W_{1..n} \), Camera Frames \( I_{t..n}, I_{t-1..n} \), Background Frames \( I_{bg,1..n} \)

**Ensure:** Top view visualisation of pedestrian motion

\[
I_{\text{Topview}} \leftarrow 0
\]

for \( i = 1 \) to \( n \) do

\[
I_{\text{OF},i} \leftarrow \text{OpticalFlow}(I_{t,i}, I_{t-1,i})
\]

\[
I_{\text{Objects},i} \leftarrow \text{ImAbsDiff}(I_{t,i} - I_{BG,i})
\]

\[
I_{\text{Edges},i} \leftarrow \text{Edge}(I_{t,i}, \text{Canny})
\]

\[
I_{\text{MeanOF},i} \leftarrow \text{MeanOpticalFlow}(I_{\text{Objects},i}, I_{\text{OF},i})
\]

\[
I_{\text{Areas},i} \leftarrow \text{AngularThreshold}(I_{\text{Edges},i}, I_{\text{OF},i}, I_{\text{Objects},i})
\]

\[
I_{\text{Topview}} \leftarrow \text{W_{camToWorld,i}}(\text{Remaining Areas, i}) + I_{\text{Topview}}
\]

end for

\[
I_{\text{Topview}} \leftarrow 1 \times (I_{\text{Topview}} > n - 1)
\]

Algorithm 2 Mean Optical Flow

**Require:** Connected Component Image \( I_{\text{Objects}} \), Optical Flow Image \( I_{\text{OF}} \)

**Ensure:** Assignment of a mean flow vector for each connected component \( I_{\text{MeanOF}} \)

\[
I_{\text{MeanOF}} \leftarrow 0
\]

for \( i = 1 \) to number of connected components in \( I_{\text{Objects}} \) do

\[
u_{i} \leftarrow 0, v_{i} \leftarrow 0
\]

\[
counter \leftarrow 0
\]

for each pixel \( p \) in \( I_{\text{Objects}} \) and component \( i \) do

\[
u_{i} \leftarrow u_{i} + u(p), v_{i} \leftarrow v_{i} + v(p)
\]

\[
counter \leftarrow counter + 1
\]

end for

\[
u_{i} \leftarrow u_{i}/\text{counter}, v_{i} \leftarrow v_{i}/\text{counter}
\]

for each pixel \( p \) in \( I_{\text{MeanOF}} \) and component \( i \) do

[Assuming components of \( I_{\text{Objects}} \)]

\[
u(p) \leftarrow u_{i}, v(p) \leftarrow v_{i}
\]

\[
counter \leftarrow counter + 1
\]

end for

end for

Fig. 4 A pedestrian captured by a Time-Of-Flight camera (first) is mapped to a top-view by finding edge segments collinear with the mean optical flow vector of the pedestrian (second) to get the overlay in the top view (third).
Table 2 Analysis and summarization of an indoor pedestrian database [27]. The input data are captured with a Time-Of-Flight Camera.

| t | t+1 | t+2 | t+3 | t+4 | t+5 | t+6 | t+7 |
|---|-----|-----|-----|-----|-----|-----|-----|

Algorithm 3 AngularThreshold

Require: Edge Image $I_{edges}$, Connected Component Image $I_{objects}$, Optical Flow Image $I_{OF}$

Ensure: Assignment of remaining areas to be mapped to top view for each connected component $I_{areas}$

$I_{areas} \leftarrow 0$

for $i = 1$ to number of connected components in $I_{objects}$ do

for each edge pixel $p$ in $I_{edges}$ and component $i$ do

$dx(p) \leftarrow \frac{1}{\pi}I_{edges}$ at $p$

$dy(p) \leftarrow \frac{1}{\pi}I_{edges}$ at $p$

if $(\text{atan2}(dy(p) - v(p), dx - u(p)) < \text{threshold})$ then

$I_{areas} \leftarrow 1$

end if

done

for each pixel $p$ in $I_{areas}$ and component $i$ do

$\text{FloodFill in Line-Sweep Manner}$ if there are two pixels $p', p''$ with value 1 in the same horizontal line in $I_{areas}$

done end for

Algorithm 4 Depth-based Top View Transformation

Require: Camera Calibration matrix $C_{depthCam}$, Camera Frames $I_{1...n}$, Background Frames $I_{bg1...n}$

Ensure: Top view visualisation of pedestrian motion

$I_{topview} \leftarrow 0$

for $i = 1$ to $n$ do

$I_{OF,i} \leftarrow \text{OpticalFlow}(I_{1...n})$

$I_{Objects,i} \leftarrow \text{ImAbsDiff}(I_{1...n} - I_{BG,i})$

$I_{Edges,i} \leftarrow \text{Edge}(I_{1...n}, \text{Canny})$

$I_{MeanOF,i} \leftarrow \text{MeanOpticalFlow}(I_{Objects,i}, I_{OF,i})$

$I_{areas,i} \leftarrow \text{AngularThreshold}(I_{Edges,i}, I_{OF,i}, I_{Objects,i})$

$\text{Reproject Depth Values}$

$I_{topview} \leftarrow C_{camToWorld,i}(I_{RemainingAreas,i}), \star (1,0,1)$

$\text{Discard Height Value}$

$I_{topview} \leftarrow 1, \star (I_{topview} > n - 1)$

done

The 4637 pedestrian (positive) samples have originally been divided into two parts for training and testing purposes in pedestrian recognition: There are 3160 positive training samples, and 1477 positive test samples. Again, we apply the motion analysis by computing the cumulative grid, Table 2 third row, and the optical flow, Table 2 fourth row.

In a third example, RGB-Cameras are used in an indoor surveillance scenario, the capturing of pedestrian motion in a train station [1]. The calibration of the cameras has been conducted with Tsai’s Algorithm by relying on equidistant markers that are placed on the floor of the...
Table 3 Analysis and summarization of an indoor pedestrian database [1]. The crowding that is noticeable at time frames $t+2$, $t+3$, $t+4$ in the input images (first row) can be directly read from the cumulative top view scatterplot (third row). An optical flow computation can be applied to the top view, e.g. to discriminate pixel movements or search for unusual motion patterns.

|   |   |   |   |   |   |   |
|---|---|---|---|---|---|---|
| $t$ | $t+1$ | $t+2$ | $t+3$ | $t+4$ | $t+5$ | $t+6$ | $t+7$ |

terminal. The distance between the markers was 1.8m (to a tolerance of ±1cm). All spatial measurements have been set in metres, again. For recording, the following cameras were used: 2x Canon MV-1 1xCCD w/progressive scan, 2x Sony DCR-PC1000E 3xCMOS (full colour, 768 x 576 pixels, 25 frames per second). The video footage has been compressed as JPEG image sequences (approx. 90% quality). The dataset displays loitering behaviour (a person standing still for longer than 60 seconds), theft of belongings and leaving luggage behind. While the lighting conditions remained stable, the density of the crowd varied with each sequence. Its outcome is visualized in Table 3.

4 Results

We have applied the algorithm described in the previous section to all three datasets to retrieve cumulative grids and optical flow maps in the topview. The results for the PETS dataset 2009 [2] are listed in Table 4. In the S1 subsets the crowding behaviour is visible in the cumulative grid. In subset S2.L3 the positions of the two people who remain still throughout the sequence are imaged with saturated dots. In subset S3.MF the motion paths of the two people in yellow vests who approach the crowd are imaged as less saturated streaks.

The results for the Depth Dataset [27] are listed in Table 5. In subset S16 the motion patterns of the three people are visible both in the cumulative grid and the optical flow map. The motion pattern of the three people moving far from the camera in subset S9 are well imaged in the optical flow map. The motion patterns of two people crossing each other may confuse the optical flow algorithm, as seen in subset S1. The results for the PETS dataset 2007 [1] are listed in Table 6. Saturated spots indicate loitering people (S1) or bags which have been dropped (S2-S8). A streak towards the spot indicates suspicious behaviour, such as theft (S5). We have compared the performance of the algorithm on the datasets for a CPU and GPU implementation, Fig. 5. The algorithm has been implemented in C++ using the OpenCV library. The CPU code was run on an Intel i7 Dual Core Processor and GPU implementation was run on a NVIDIA GeForce GTX 690 with 2048Mb Cache, 1536 cores, and NVIDIA Driver 4.20. We compared the framerate in fps against the routine at idle, i.e. reading in the image streams without processing (no operation). It can be seen, that with the GPU implementation we can achieve real-time framerates (greater than 10 fps) that enable the pedestrian surveillance in top view with life cumulative maps. As all eight cameras were processed, the outdoor dataset [2] is the most consuming whereas the indoor depth dataset [27] with a single input stream is the least consuming.

5 Conclusion

We have presented an approach to retarget pedestrian surveillance footage into the topview in order to perform motion and video analysis to it. Two algorithms, one for RGB-data and one for depth data have been described in detail. The motion analysis consisted of cumulative maps to help crowding detection and the application of optical flows. We have applied the algorithm to an RGB outdoor
Table 4 The results of our algorithm applied to different sequences of the PETS dataset 2009 [2]

| PETS dataset 2009 [2] | The sequence contains a medium density crowd, who are running. There are overcast lighting conditions | The cumulative grid shows the occupied area by the moving crowd in the middle of the sequence. |
|----------------------|-------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------|
| S1.L1                | The sequence contains a high density crowd, who are walking in diverse directions. There are bright sunshine and shadows | The area occupied by the crowd is visible in the cumulative grid in the middle of the sequence. |
| S1.L2                | The sequence contains a high density crowd, who are walking. There are bright sunshine and shadows | The scattered incoherent crowd movements are visible in the less saturated grid. |
| S1.L3                | The sequence contains a sparse crowd, who are walking. There are overcast lighting conditions visible | The flows towards the scene center are recognisable in the cumulative grid and the flow map. |
| S2.L1                | The sequence contains a medium density crowd, who are walking. There are bright sunshine and shadows visible | In the grid, two saturated spots denote the position of the two men remaining still while the walking crowd is imaged in a less saturated region. |
| S2.L2                | The sequence contains a medium density crowd, who are walking. There are bright sunshine and shadows visible | Two disjunct streaks from the bottom to the top left of the grid indicate the paths of the men in yellow vest who are approaching the main crowd, which walks towards the scene centre. |
| S2.L3                | The sequence contains a high density crowd, who are running. There are bright sunshine and shadows visible | Two disjunct streaks from the bottom to the top left of the grid indicate the paths of the men in yellow vest who are approaching the main crowd, which walks towards the scene centre. |
| S3.HL                | The sequence contains a high density crowd, who are running. There are bright sunshine and shadows visible | Two disjunct streaks from the bottom to the top left of the grid indicate the paths of the men in yellow vest who are approaching the main crowd, which walks towards the scene centre. |
| S3.MF                | The sequence contains a high density crowd, who are performing different activities. There are overcast lighting conditions visible | Two disjunct streaks from the bottom to the top left of the grid indicate the paths of the men in yellow vest who are approaching the main crowd, which walks towards the scene centre. |

Dataset consisting of eight calibrated cameras and two indoor datasets. One dataset was a depth-based dataset consisting of one ToF-camera, the other was the surveillance of a train station with for extrinsically calibrated RGB cameras.

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Table 5 The results of our algorithm applied to different sequences of the Depth Dataset [27]

| Depth Dataset [27] | The sequence contains two people. One leaves the scene, one remains at his position. | The cumulative grid shows the trail of the one person moving from the scene and a blue saturated spot indicates that the other person remains still. |
|--------------------|----------------------------------------------------------------------------------|----------------------------------------------------------------------------------|
| S2                 | The sequence contains one person who is moving quickly away from the camera       | The cumulative grid shows the trail of his body positions.                      |
| S4                 | The sequence contains one person who is moving quickly parallel to the image plane | The cumulative grid shows the trail of his body positions.                      |
| S6                 | The sequence contains two people. One moves away to the left, the other moves a bit to the camera | The cumulative grid shows the trail of both body positions.                     |
| S9                 | The sequence contains three people. One vanishes to the rear right, one moves parallel to the image plane towards the right and one remains still | The cumulative grid shows the trail of all three body positions.                |
| S13                | The sequence contains one person who slowly moves from the rear left towards the scene centre. | The slight fainted trail indicates the motion.                                   |
| S16                | The sequence contains three people. One moves towards the camera, the second moves to the right, while the third remains still at the rear left. | The two trails are clearly visible, one spot indicates the person standing still. |
| S19                | The sequence contains one person who quickly moves towards the camera.            | The less saturated trail indicates a fast paced motion.                         |
| S22                | The sequence contains one person who quickly moves from rear left to rear right.  | The trail is visible in the upper part of the grid.                            |

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Fig. 5 The performance analysis for CPU vs. CUDA-accelerated implementations of the algorithm. We tested the algorithm with the three datasets. Since eight cameras have to be processed, the outdoor dataset [2] is the most consuming whereas the indoor depth dataset [27] with a single input stream is the least consuming. The GPU based implementation outperforms a purely CPU-based implementation and approximates an idle loop (no processing) more closely.
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| PETS dataset 2007 [1] | The results of our algorithm applied to different sequences of the PETS dataset 2007 [1] |
|----------------------|--------------------------------------------------------------------------------------------|
| S1                   | The sequence contains one person who enters the scene and then loiters and leaves the scene. |
|                      | In the cumulative grid with moving average $A_t, t_{span} = 100$ the position of the loitering person emerges visually. |
| S2                   | The sequence contains a person who walks into the scene and puts a bag on the ground. After loitering the person exits. |
|                      | The loitering is visible in the cumulative map as blue saturated pixel set. The position of the bag becomes visible in the cumulative map from the moment of positioning until the end of the sequence. |
| S3                   | The sequence contains two people who enter the scene. One places a bag on the ground. The second person picks up the bag and both walk out. |
|                      | Small saturated pixel regions in cumulative grid with moving average $A_{t, t_{span}} = 100$ indicate loitering of the two people. The optical flow map shows two spots diverging in different directions. |
| S4                   | The sequence contains four people who walk into the scene. One places a bag to the ground, another picks up the bag and all walk out of the scene. |
|                      | The loitering is visible in the cumulative grid with moving average $A_{t, t_{span}} = 100$ as blue saturated pixel set. |
| S5                   | The sequence contains one person who the scene. They place the bag on the ground. A second person (thief) picks up the bag and walks out of the scene. |
|                      | In the cumulative grid with moving average $A_{t, t_{span}} = 200$, the bag and the owner are visible as blob, with the more saturated pixel set showing the bag. The thieves approaching motion is seen in a less saturated second blob, that streaks towards the bag. |
| S6                   | The sequence contains two people. They place bags down on the ground. Two other people conduct theft and distraction. |
|                      | Saturated blob in the cumulative grid with moving average $A_{t, t_{span}} = 300$ where the two people stand. |
| S7                   | The sequence contains a single person with two bags. They place one bag on the ground, leave and return to pick up the left bag. |
|                      | Saturated blob in the cumulative grid with moving average $A_{t, t_{span}} = 100$ where the person with the luggage stands. |
| S8                   | The sequence contains a person who places a large bag on the ground. He leaves the bag for a short moment before walking away with it. |
|                      | Saturated blob in the cumulative grid with moving average $A_{t, t_{span}} = 100$ where the abandoned luggage lays. |