Auto-SDA: Automated Video-based Social Distancing Analyzer

Mahshid Ghasemi, Zoran Kostic, Javad Ghaderi, Gil Zussman

Electrical Engineering, Columbia University
{mahshid.Ghasemi,zk2172,jghaderi,gil.zussman}@columbia.edu
COVID-19 and Social Distancing

KEEP A SAFE DISTANCE
Social Distancing Analysis Using the COSMOS Testbed

Automated video-based Social Distancing Analyzer (Auto-SDA)

- Measures compliance with social distancing policies.
- Evaluated using the COSMOS testbed deployed in West Harlem, NYC.
- Used a camera deployed on the 2nd floor of Columbia’s Mudd building looking at the COSMOS site¹.

¹https://wiki.cosmos-lab.org/wiki/Hardware/Cameras
Automated Social Distancing Analyzer (Auto-SDA)

- **Calibration**: Converts 2D on-image distances to 3D on-ground distances.
- **Object detection and tracking**: Locates the pedestrians and assigns an ID to each of them.
- **ID correction**: Removes the redundant IDs generated by the tracker and extract the trajectory of each pedestrian.
- **Group detection**: Excludes the pedestrians affiliated with a single social group from social distancing violations.
Multi-area Camera Calibration: Intrinsic Parameters

- Camera calibration is **required** to convert 2D on-image distances to 3D on-ground distances.
- Camera calibration means calculating the **intrinsic** and **extrinsic** parameters of the camera.
- Intrinsic parameters can be obtained using a **checkerboard**.
- Intrinsic parameters **does not** depend on view point of the camera.
- More than 20 images of the checkerboard in different poses were provided to the OpenCV library to obtain the intrinsic parameters of the camera.

Calibration of the COSMOS cameras using a checkerboard:
Multi-area Camera Calibration: Extrinsic Parameters

- Standard camera calibration methods lead to inaccurate on-ground distance computation.
- Calibration module splits the view of the camera into multiple areas.
- The extrinsic parameters for each area are computed individually.
- Multi-area camera calibration can obtain on-ground distances with less than 10 cm error.

<table>
<thead>
<tr>
<th>Pixel Coordinates of a Pair of Points on a 4K Frame</th>
<th>Calculated Distance from Different Methods (cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ground-truth: 320 cm</td>
<td>Multi-area Calibration: 325 cm</td>
</tr>
<tr>
<td>Ground-truth: 183 cm</td>
<td>Multi-area Calibration: 178 cm</td>
</tr>
<tr>
<td>Ground-truth: 503 cm</td>
<td>Multi-area Calibration: 508 cm</td>
</tr>
<tr>
<td>Ground-truth: 259 cm</td>
<td>Multi-area Calibration: 256 cm</td>
</tr>
<tr>
<td>Ground-truth: 320 cm</td>
<td>Multi-area Calibration: 314 cm</td>
</tr>
</tbody>
</table>
• **High altitude** and **oblique view** of traffic cameras (including the COSMOS camera), and **obstacles** degrade the performance of the tracker.
• Compensates for the inaccuracies of the tracker.
• **Removes the redundant IDs** and extracts the **entire trajectory** of the pedestrians.
• Uses **Linear Regression (LR)** to find trajectory segments.

---

**Algorithm 1 ID Correction**

```
1: Input: $ID_{vec}, e_1, e_2, n$  \quad \triangleright \quad ID_{vec}$ is the output of NvDCF tracker
2: Output: corrected $ID_{vec}$
3: for $id \in ID_{vec}$ do
4:     Compute $id.Traj$ \quad \triangleright \quad vector of points on id’s path
5:     Compute $id.TimeStamp.StartTime$ \quad \triangleright \quad detection time
6:     Compute $id.TimeStamp.StopTime$ \quad \triangleright \quad Lost time
7:     Compute $(id.TailEst, id.TailDir)$ \quad \triangleright \quad Linear Regression of $id.Trj.tail(n)$
8:     Compute $(id.HeadEst, id.HeadDir)$ \quad \triangleright \quad Linear Regression of $id.Trj.head(n)$
9: for $(id_1, id_2) \in ID_{vec}$ do
10:    $t_1 \leftarrow id_1.TimeStamp.StartTime$
11:    $t_2 \leftarrow id_2.TimeStamp.StartTime$
12:    $p_1 \leftarrow id_1.TailEst.at(t = t_2)$, \quad $p_2 \leftarrow id_1.Trj.at(t_2)$
13:    $v_1 \leftarrow id_1.TailDir$, \quad $v_2 \leftarrow id_2.HeadDir$
14:    if $t_2 - t_1 < e_1$ \&\& $|p_1 - p_2| < e_2$ \&\& $\angle (v_1, v_2) < 90^\circ$ then
15:        $id_1$ and $id_2$ belongs to same person
```
Group Detection

- Excludes social groups from social distancing violation.
- **Off-the-shelf group detectors** require detailed information such as body and head orientation, velocity, exact trajectory, etc.
- In realistic deployments, such as COSMOS cameras, **details cannot be obtained**.
- **Detects** the social groups **with limited data** from the cameras.

Demonstration of the group detection algorithm on a recorded video from the camera on the 2nd floor of Columbia Mudd building.

Algorithm 2 Group Detection

1: Input: $ID_{vec}, d_{max}, a_{max}, \sigma_{max}$
2: Output: $ID_{vec}$ Pedestrians belong to a group
3: for $id \in ID_{vec}$ do
4:     $id.TimeTrj = map(id.TimeStepVec, id.Trj)$
5: for $(id_1, id_2) \in ID_{vec}$ do
6:     $n = 0$
7: for $t = 1 : T$ do
8:     $pos_1 = id_1.TimeTrj(t), pos_2 = id_2.TimeTrj(t)$
9:     $d = ||pos_1 - pos_2||_2$
10: if $d > d_{max}$ then
11:     $n +=$, continue
12:     $Corr_{vec}(id_1, id_2).append(d)$
13: if $n > N_{max}$ then
14:     continue
15: $\bar{d} = mean(Corr_{vec}(id_1, id_2))$ \(\triangleright\) calculate the mean distance between two pedestrians
16: $\sigma = std(Corr_{vec}(id_1, id_2))$ \(\triangleright\) calculate the standard deviation of instantaneous distances between two pedestrians
17: if $\bar{d} < \bar{d}_{max}$ && $\sigma < \sigma_{max}$ then
18:     $id_1$ and $id_2$ belongs to the same group
## Comparison of Prior Work to Auto-SDA

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>[1, 2]</td>
<td>✓</td>
<td>✗</td>
<td>Homography</td>
<td>⩾ 10 cm</td>
<td>✗</td>
<td>✗</td>
<td>✗</td>
</tr>
<tr>
<td>[3]</td>
<td>✓</td>
<td>✓</td>
<td>Pairwise L₂ norm</td>
<td>⩾ 10 cm</td>
<td>✗</td>
<td>✗</td>
<td>✗</td>
</tr>
<tr>
<td>[4]</td>
<td>✓</td>
<td>✓</td>
<td>Planar camera</td>
<td>⩾ 10 cm</td>
<td>✗</td>
<td>✗</td>
<td>✗</td>
</tr>
<tr>
<td>[4, 5, 6, 7]</td>
<td>✓</td>
<td>✗</td>
<td>Planar camera</td>
<td>⩾ 10 cm</td>
<td>✗</td>
<td>✗</td>
<td>✗</td>
</tr>
<tr>
<td>Auto-SDA</td>
<td>✓</td>
<td>✓</td>
<td>Multi-area</td>
<td>&lt; 10 cm</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

Measurements and Evaluation

• Evaluating the **impact of COVID-19 on pedestrians** behavior using recorded videos from the COSMOS camera.

• Recorded videos consist of:
  ○ **Pre-pandemic** videos that were opportunistically recorded before the pandemic in **June 2019**.
  ○ **Pandemic** videos recorded between **June 17 to July 20, 2020** (soon after the lockdown).
  ○ **Post-vaccine** videos recorded in **May 2021** (after the vaccine became broadly available).
Impact of the Pandemic on Pedestrians’ Density

- Density of the pedestrians has **decreased after the lockdown** (compared to pre-pandemic).
- After the availability of the **vaccine** the density has **slightly increased**.
  - **Pre-pandemic**, i.e., June, 2019
  - **Pandemic**, i.e., June-July, 2020
  - **Post-vaccine**, i.e., May, 2021

![Bar chart showing pedestrian density](chart.png)
Compliance with Social Distancing Protocols

- Social distancing violation: when a pedestrian maintains less than 6 ft distance from other pedestrians with whom he/she is not walking.
- Percentage of social distancing violators (average, std):
  - Pandemic, i.e., June-July, 2020: (36.2, 17.88).
  - Post-vaccine, i.e., May, 2021: (40.34, 19.87).

Normalized histogram of the percentage of pedestrians considered social distancing violators in the recorded videos.
Compliance with Social Distancing Protocols

Measurements of social distancing violation time (average, std):

- **Pandemic**, i.e., June-July, 2020: (10, 7.94) s.
- **Post-vaccine**, i.e., May, 2021: (10.34, 9.14) s.

Normalized histogram of duration of the social distancing violations incidents.
Compliance with Social Distancing Protocols

Percentage of pedestrians affiliated with a social group (average, std):

- **Post-vaccine**, i.e., May, 2021: (22.03, 10.15).

Normalized histogram of duration of percentage of pedestrians in a social group.
Conclusion and Future Work

Auto-SDA modules enable a generic object detection and tracker model to be used as a social distancing analyzer system:

- **Multi-area calibration** computes the on-ground distances between pedestrians with high accuracy.
- **ID correction** rectifies the output of the tracker model.
- **Group detection** excludes social groups from social distancing violation.
- Used **real-word videos** to evaluate the system and measure the impact of social distancing policies on pedestrian’s social behavior.

Future work:

- Design and implementation of **privacy-preserving** methods.
  - Extension of Auto-SDA (B-SDA) will be presented in the demo session which uses **bird’s eye view camera**.
- Integration of information from **multiple cameras** and sensors.
- Design of real-time algorithms, and extensive evaluation as the social distancing policies change.