

## Abstract

Social distancing can reduce the spread of coronavirus. Hence, we designed two approaches for social distancing analysis, **Automated video-based Social Distancing Analyzer (Auto-SDA)**, and **Bird's eye view Social Distancing Analyzer (B-SDA)**.

- Designed to measure pedestrians' compliance with social distancing policies using **street-level** and **bird's eye view** cameras.
- Auto-SDA offers high accuracy which is not sensitive to the dynamics of the scene and the camera's tilt angle.
- B-SDA provides comparable accuracy while preserving pedestrian's privacy.
- Evaluated the pipelines using **COMOS testbed** deployed in West Harlem, NYC.
- Used real-world videos recorded from cameras deployed on the **2<sup>nd</sup>** and **12<sup>th</sup>** floor of **Columbia's Mudd building**, looking at the COSMOS site, before and during the pandemic.
- The results represent how the impact of social distancing policies on pedestrian's social behavior.

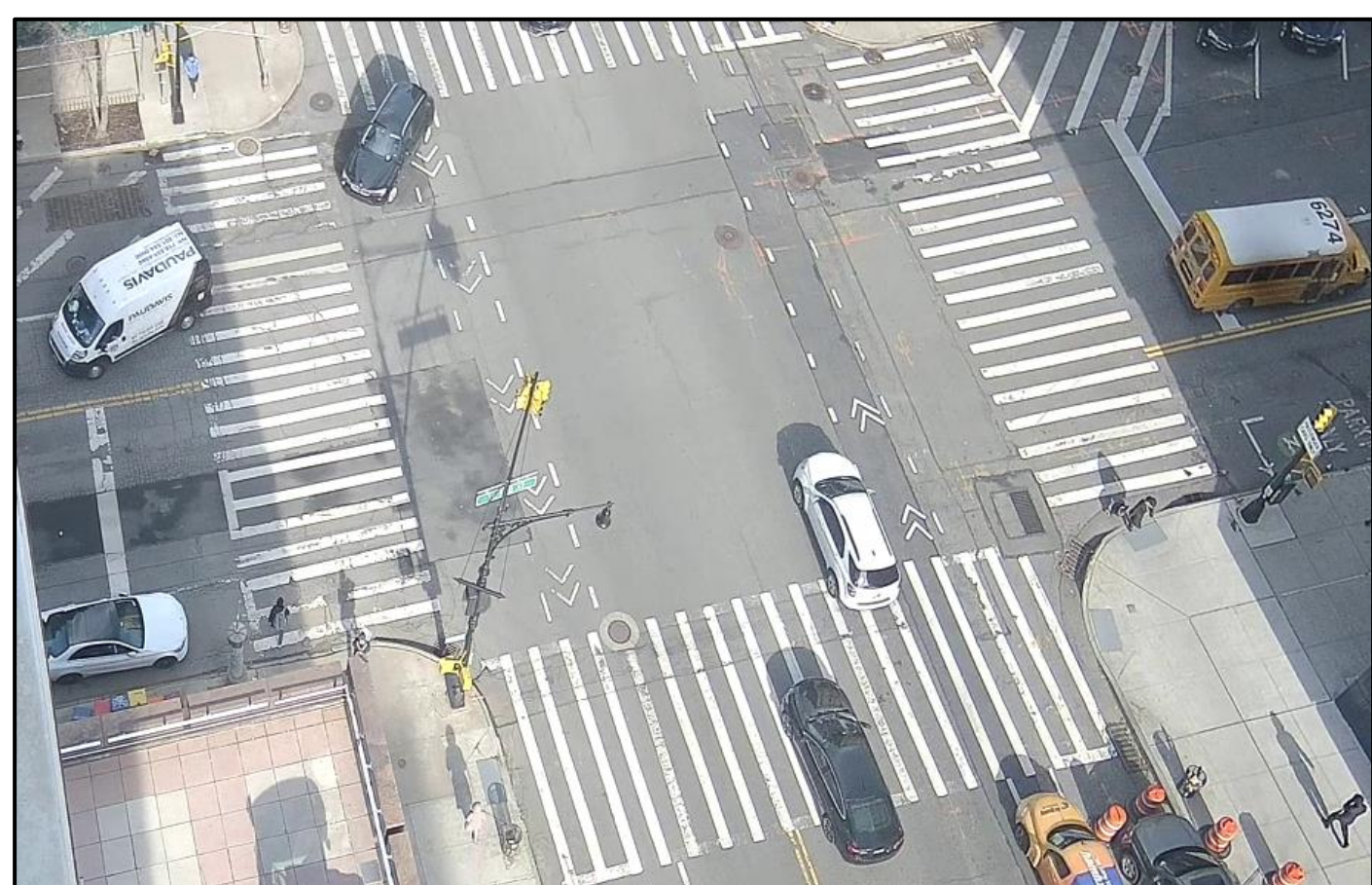
## COSMOS Testbed Pilot Site



The NSF PAWR COSMOS site at 120<sup>th</sup> St. and Amsterdam Ave. intersection, NYC.

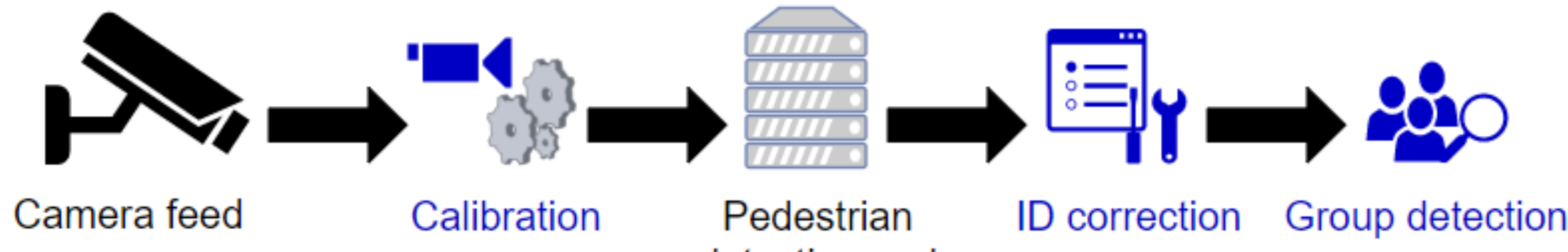


Viewpoint of the camera deployed on the 2<sup>nd</sup> floor of the Columbia's Mudd building.



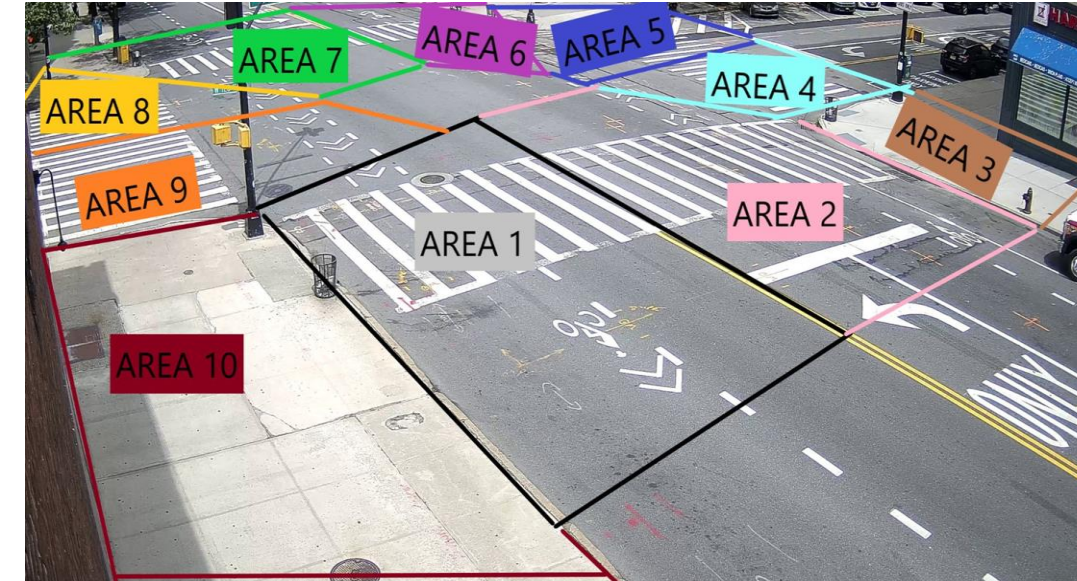
Viewpoint of the camera deployed on the 12<sup>th</sup> floor of the Columbia's Mudd building.

## Automated Social Distancing Analyzer (Auto-SDA)

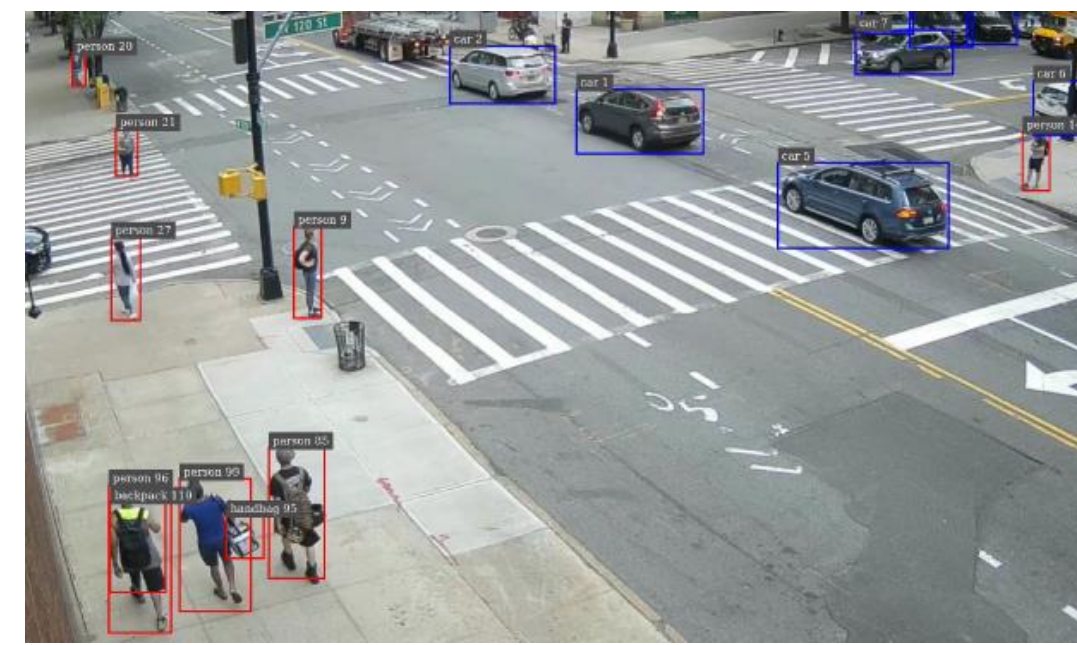


### Calibration:

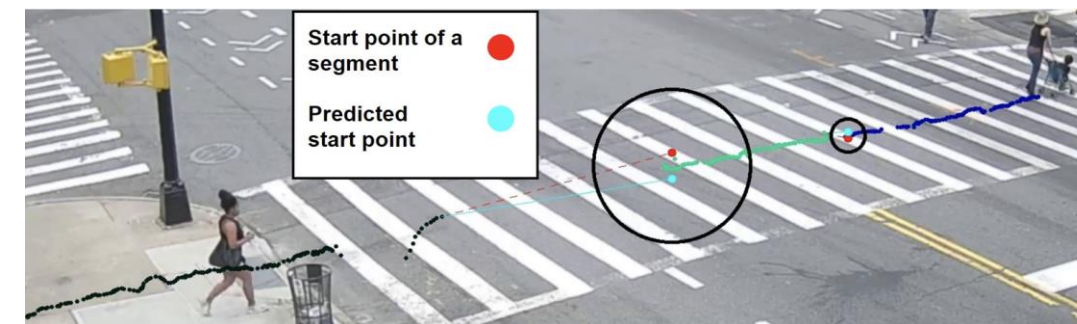
- Converts 2D on-image distances to 3D on-ground distances.
- Standard camera calibration methods lead to **inaccurate on-ground distance** computation.
- Auto-SDA's calibration module **splits the view** of the camera into **multiple areas**.
- Photogrammetry parameters are calculated for each area individually.
- Auto-SDA's calibration module can obtain on-ground distances with **less than 10 cm error**.



The view of the camera is split to 10 areas. The extrinsic parameters are calculated for each area individually.



Results of object detection (YOLOv4) and tracking (Nvidia DCF).



ID correction detects and removes redundant IDs when the tracker assigns 3 IDs to a single pedestrian.



Group detection using instantaneous distance between pedestrians.

### Object detection and tracking:

- Uses **Nvidia DeepStream SDK** platform which is an **optimized architecture** built using the **Gstreamer** framework.
- Uses object detector, **YOLOv4**, and **Nvidia DCF-based** tracker models.
- ID correction:**
  - High altitude** and **oblique** view of the COSMOS cameras, and **obstacles** degrade the performance of the tracker.
  - Compensates for the inaccuracies of the tracker.
  - Removes the redundant IDs** and extracts pedestrians' **entire trajectory**.

### 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.

## Comparison of Prior Work to Auto-SDA

Framework	Object Detection	Tracking	Calibration Method	On-Ground Distance Computation Error	Correction	Group Detection	Real-World COVID-19 Pandemic Impact Analysis
[1, 2]	✓	✗	Homography transformation	$\gg 10$ cm	✗	✗	✗
[3]	✓	✓	Pairwise $L_2$ norm	$\gg 10$ cm	✗	✗	✗
[4]	✓	✓	Planar camera persp. trans.	$\gg 10$ cm	✗	✗	✗
[4, 5, 6, 7]	✓	✗	Planar camera persp. trans.	$\gg 10$ cm	✗	✗	✗
Auto-SDA	✓	✓	Multi-area calibration	$< 10$ cm	✓	✓	✓

## Auto-SDA Algorithms

### Algorithm 1 ID Correction

```

1: Input:  $ID_{acc}, e_1, e_2, n$   $\rightarrow ID_{acc}$  is the output of NvDCF tracker
2: Output: corrected  $ID_{acc}$ 
3: for  $id \in ID_{acc}$  do
4:   Compute  $id.Trj$   $\rightarrow$  vector of points on id's path
5:   Compute  $id.Timestamp.StartTime$   $\rightarrow$  detection time
6:   Compute  $id.Timestamp.StopTime$   $\rightarrow$  Lost time
7:   Compute  $(id.TailEst, id.TailDir) \leftarrow$  Linear Regression of  $id.Trj.tail(n)$ 
8:   Compute  $(id.HeadEst, id.HeadDir) \leftarrow$  Linear Regression of  $id.Trj.head(n)$ 
9:   for  $(id_1, id_2) \in ID_{acc}$  do
10:     $t_1 \leftarrow id_1.Timestamp.StartTime$ 
11:     $t_2 \leftarrow id_2.Timestamp.StartTime$ 
12:     $p_1 \leftarrow id_1.TailEst.at(t = t_1)$ ,  $p_2 \leftarrow id_2.Trj.at(t_2)$ 
13:     $o_1 \leftarrow id_1.TailDir$ ,  $o_2 \leftarrow id_2.HeadDir$ 
14:    if  $t_2 - t_1 < \epsilon$  &&  $\|p_1 - p_2\| < \epsilon$  &&  $\angle(o_1, o_2) < 90^\circ$  then
15:       $id_1$  and  $id_2$  belongs to same person

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### Algorithm 2 Group Detection

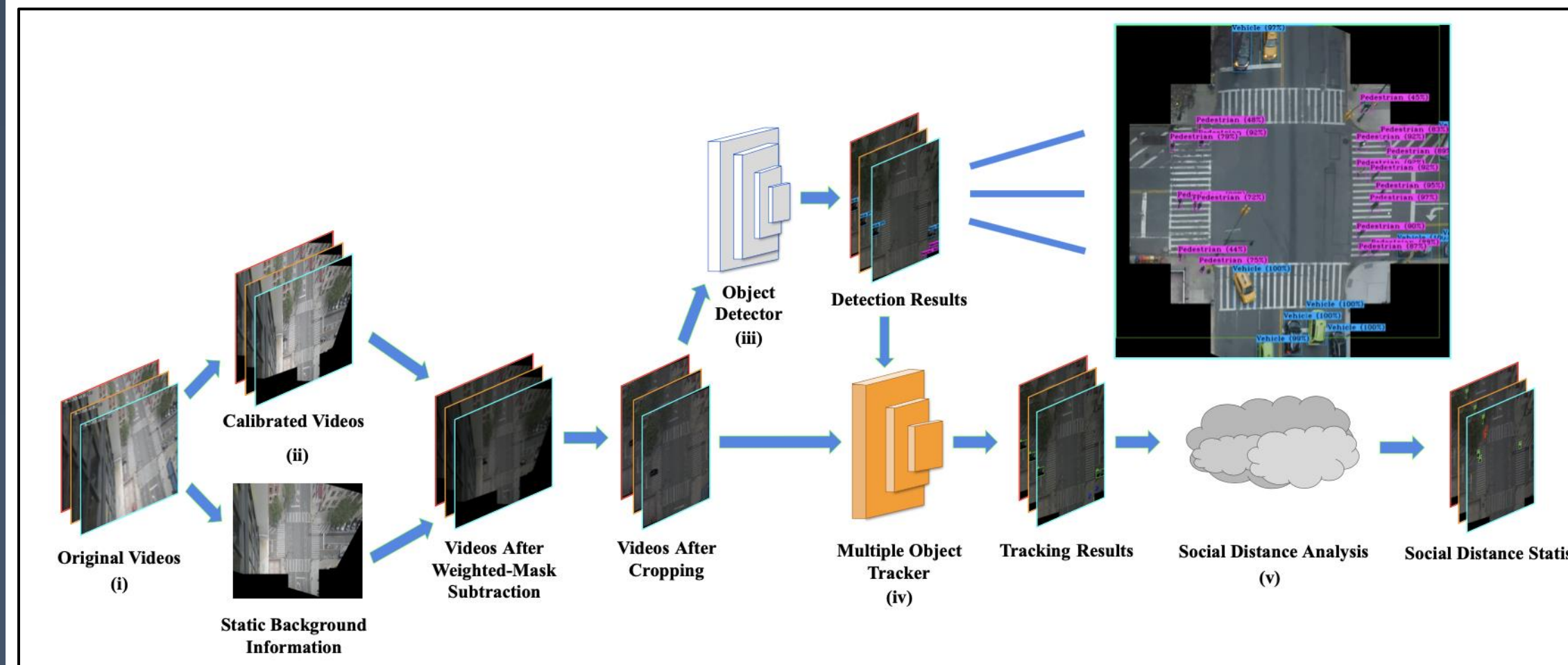
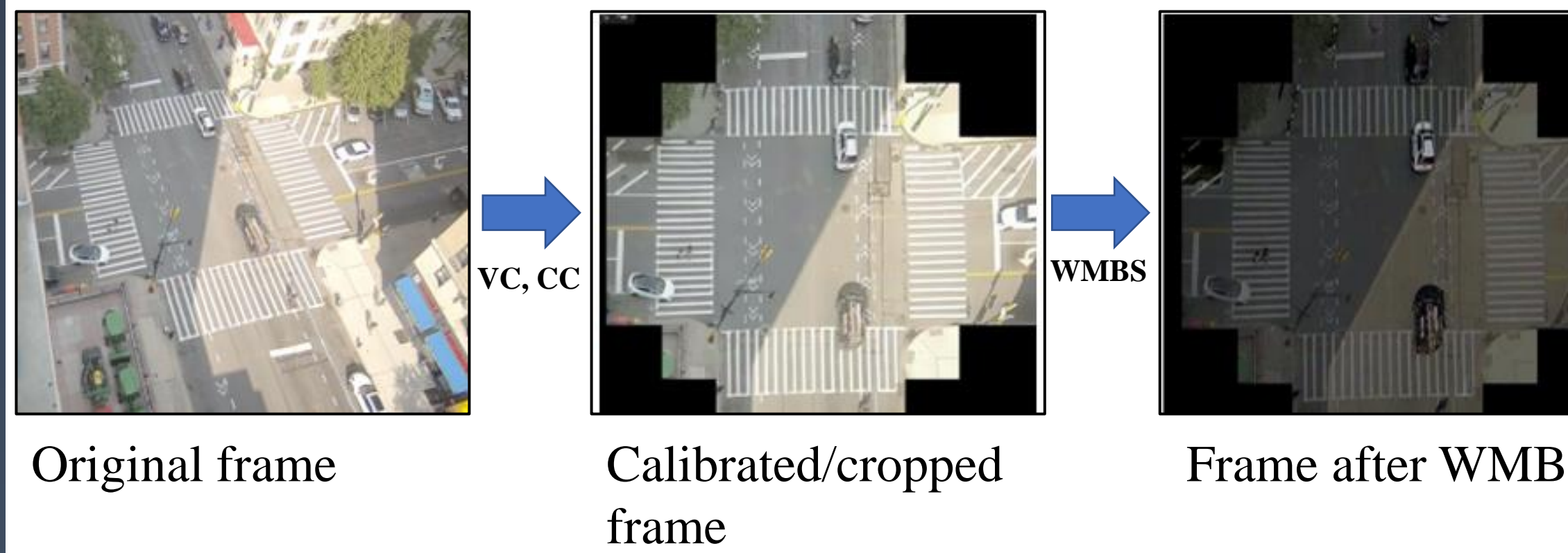
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1: Input:  $ID_{acc}, d_{max}, d_{min}, \sigma_{max}$ 
2: Output:  $ID_{acc}$ , Pedestrians belong to a group
3: for  $id \in ID_{acc}$  do
4:    $id.TimeTrj = \text{map}(id.TimestampVec, id.Trj)$ 
5:   for  $(id_1, id_2) \in ID_{acc}$  do
6:      $n = 0$ 
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:        continue
12:       $Corr_{acc}(id_1, id_2).append(d)$ 
13:      if  $n > N_{min}$  then
14:        continue
15:       $\bar{d} = \text{mean}(Corr_{acc}(id_1, id_2))$   $\rightarrow$  calculate the mean distance between two pedestrians
16:       $\sigma = \text{std}(Corr_{acc}(id_1, id_2))$   $\rightarrow$  calculate the standard deviation of instantaneous distances between two pedestrians
17:      if  $\bar{d} < d_{max}$  &&  $\sigma < \sigma_{max}$  then
18:         $id_1$  and  $id_2$  belongs to the same group

```

## Bird's Eye View Social Distancing Analyzer (B-SDA)

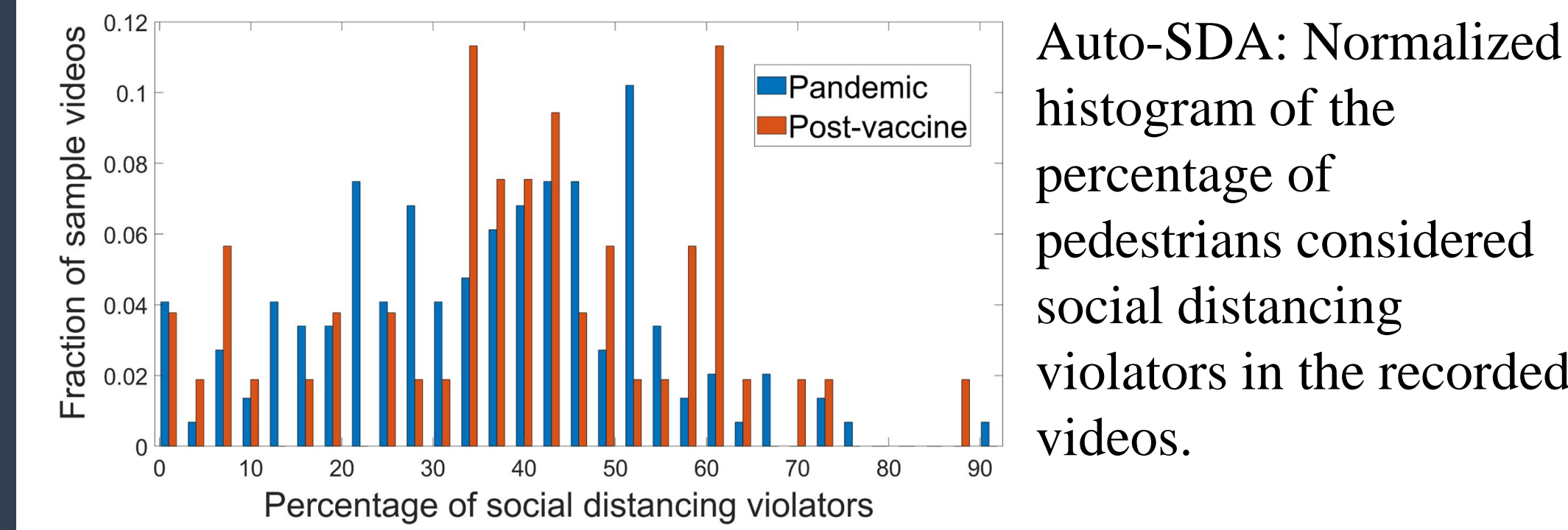
- Auto-SDA** detects social distancing violations with **high accuracy**.
- Street-level cameras' challenges:
  - Surveillance area is limited.
  - Temporal tracking of pedestrians is challenging due to occlusions.
  - Street-level cameras may raise privacy concerns.
- B-SDA modules:**
  - Pre-processing**
    - Video Calibration (**VC**): Transforms original (slanted) view to perpendicular to the ground.
    - Center Cropping (**CC**): Crops the salient part of the image.
    - Weighted-Mask Background Subtraction (**WMBS**): Background image is subtracted from the original frames to sharpen the boundaries between pedestrians and the static background.
  - Pedestrian detection and tracking:
    - Customized YOLOv4** (detector) to enhance the detection of small pedestrians.
    - SORT** (tracker).
  - Group detection**: Similar to the group detection module in Auto-SDA.



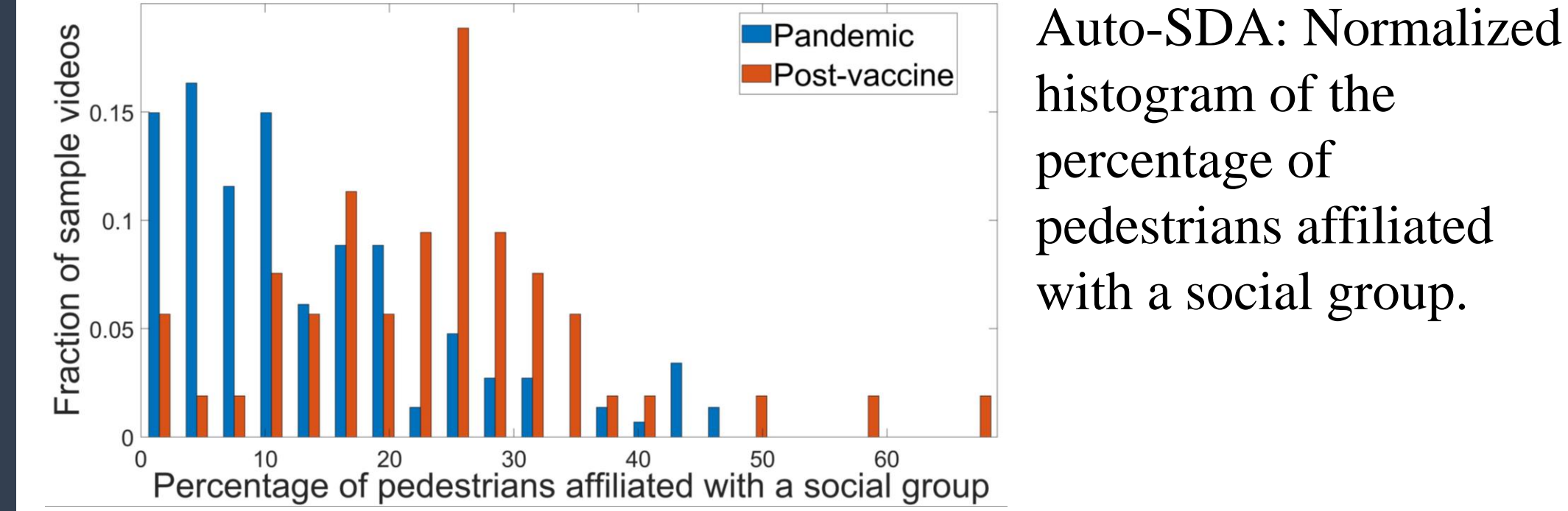
B-SDA pipeline: (i) collect raw videos from a bird's-eye view camera; (ii) do calibration and background subtraction to alleviate the effect of sub-optimal sensor quality; (iii) get pedestrian detection results; (iv) get pedestrian tracking information; (v) analyze pedestrian movement behavior with social distancing analysis algorithm.

## Measurements and Evaluation

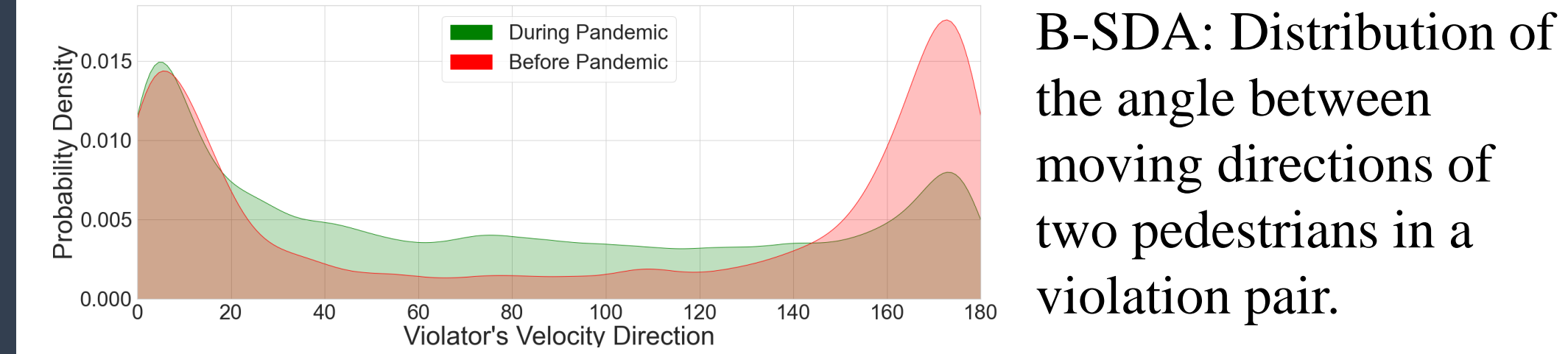
- Evaluated the **impact of COVID-19 on pedestrians behavior** using recorded videos from the COSMOS cameras.
- Recorded videos consist of:
  - Pre-pandemic** videos recorded in **June 2019**.
  - Pandemic** videos recorded between **June 17 to July 20, 2020 (soon after the lockdown)**.
  - Post-vaccine** videos recorded in **May 2021 (after the vaccine became broadly available)**.



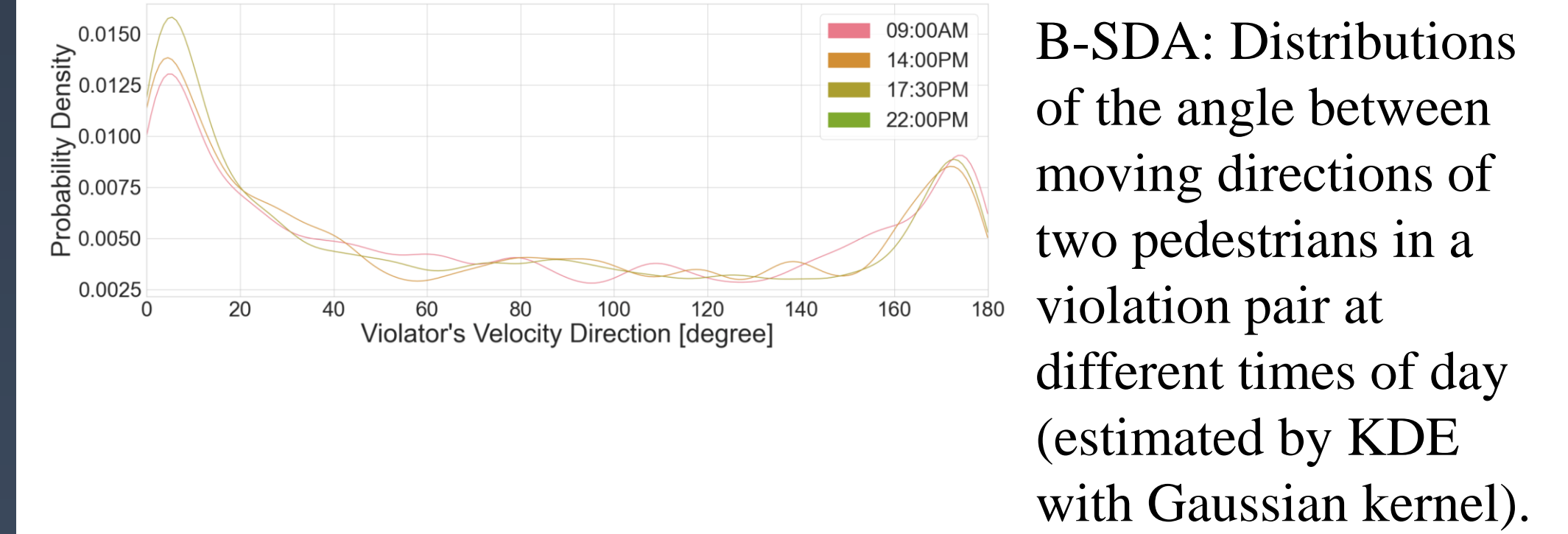
Auto-SDA: Normalized histogram of the percentage of pedestrians considered social distancing violators in the recorded videos.



Auto-SDA: Normalized histogram of the percentage of pedestrians affiliated with a social group.



B-SDA: Distribution of the angle between moving directions of two pedestrians in a violation pair.



B-SDA: Distributions of the angle between moving directions of two pedestrians in a violation pair at different times of day (estimated by KDE with Gaussian kernel).

## References

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