Paper:

Tsukuba Challenge 2017 Dynamic Object Tracks Dataset for Pedestrian Behavior Analysis

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Navigation in social environments, in the absence of traffic rules, is the difficult task at the core of the annual Tsukuba Challenge. In this context, a better understanding of the soft rules that influence social dynamics is key to improve robot navigation. Prior research attempts to model social behavior through microscopic interactions, but the resulting emergent behavior depends heavily on the initial conditions, in particular the macroscopic setting. As such, data-driven studies of pedestrian behavior in a fixed environment may provide key insight into this macroscopic aspect, but appropriate data is scarcely available. To support this stream of research, we release an open-source dataset of dynamic object trajectories localized in a map of 2017 Tsukuba Challenge environment. A data collection platform equipped with lidar, camera, IMU, and odometry repeatedly navigated the challenge's course, recording observations of passersby. Using a background map, we localized ourselves in the environment, removed the static background from the point cloud data, clustered the remaining points into dynamic objects and tracked their movements over time. In this work, we present the Tsukuba Challenge Dynamic Object Tracks dataset, which features nearly 10,000 trajectories of pedestrians, cyclists, and other dynamic agents, in particular autonomous robots. We provide a 3D map of the environment used as global frame for all trajectories. For each trajectory, we provide at regular time intervals an estimated position, velocity, heading, and rotational velocity, as well as bounding boxes for the objects and segmented lidar point clouds. As additional contribution, we provide a discussion which focuses on some discernible macroscopic patterns in the data.

Keywords: Tsukuba Challenge, dataset, detection, tracking

1. Introduction

The annual Tsukuba Challenge offers a unique environment to test the autonomous capabilities of a robotic vehicle. Since the beginning of the challenge in 2007 [1], the overarching goal is to assess autonomous robots' capability to handle real-world scenarios by having them navigate an unmodified course full of pedestrians, cyclists and other agents, some behaving naturally and others interacting with the robots. The 2017 challenge consisted of autonomously navigating through an area of over two kilometres, going through a park, pedestrian walkway and both indoors and outdoors shopping malls. This general course for the challenge was determined beforehand, but it remains up to the participants to decide their specific trajectory through a course that varies wildly: from large, open spaces to narrow corridors, as shown in **Fig. 1**. As previously mentioned, the course is often dense with other agents: adults, children, dogs, bicycles, small motorized vehicles, and of course robots. While many agents are acting in completely natural manner, the environment also includes passersby interesting in interacting with the robots, as well as also robot operators and safety officials. The sheer quantity and chaotic nature of these agents makes this area of Tsukuba a particularly challenging and interesting test environment for autonomous navigation.

Familiar problems need to be addressed to autonomously navigate the Tsukuba Challenge environment successfully: global localization, global and local path planning, object detection and tracking, as well as avoidance capabilities. While strategies to solve these problems differ, addressing these issues represents a minimum requirement for an autonomous mobile system in any sort of environment, though the constraints may change with the environment. In particular, autonomous cars on a road network are constrained both by the vehicle dynamics and the trajectories that comply with traffic rules. Since all cars are bound by nearly identical constraints, their behavior is generally predictable. In comparison, dynamic agents in the Tsukuba Challenge environment move at much slower speeds than cars but are far less predictable

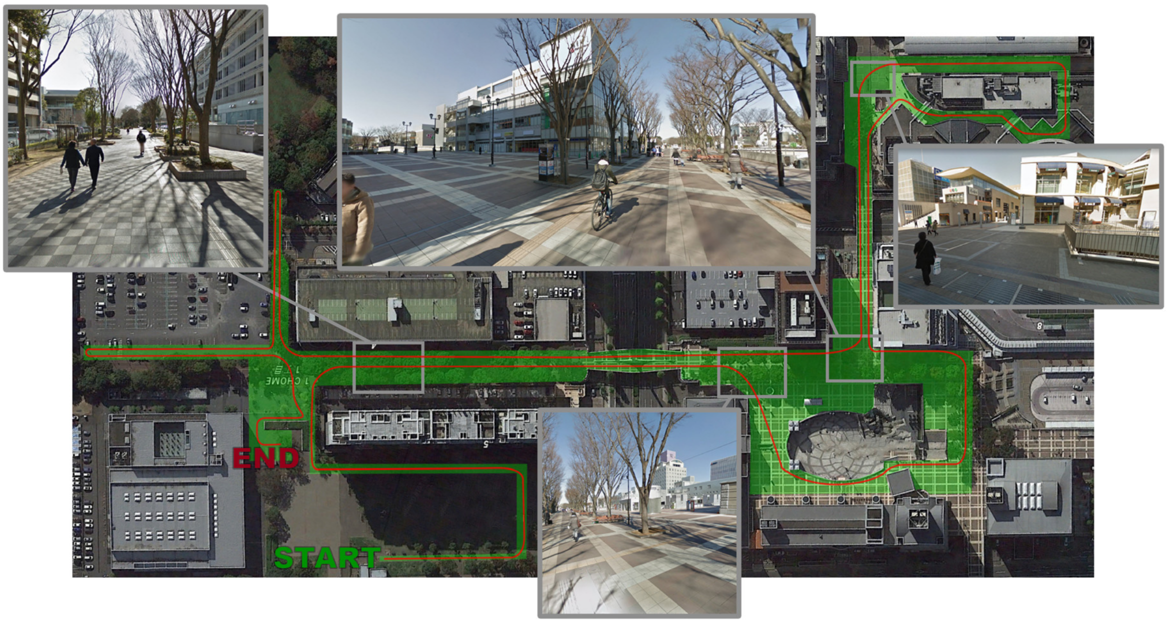


Fig. 1. Top view of the course through the 2017 Tsukuba Challenge environment, with our approximate target trajectory in red. In green, we show approximately the available, *traversable* terrain, disregarding small obstacles (trees, cones, tables, etc.) in this area. We also show images of various key areas to show the available navigation space.

as there are no hard rules which constrain their motion. Unlike road networks, all traversable terrain can be used by any agent without restrictions, which makes our navigation task significantly more difficult. In **Fig. 1**, we show in green the large amount of free space available in the environment to demonstrate the leeway we have in planning our specific trajectory. This extra degree of freedom in the planning stage is difficult to optimize, because of the lack of hard rules makes it difficult to predict how other agents might traverse the environment. The strategy used by our navigation system is therefore to simply plan a navigation route based solely on static objects and deal with dynamic obstacles when they are encountered.

This simple approach may be sufficient for the challenge, but it seems far from optimal. In practice, our vehicle was considerably slowed down by incoming traffic, and disturbed the natural flow of pedestrian. Ideally, we should acknowledge in our navigation strategy that other agents in the environment have the same goal: achieving their destination safely and without complication. Indeed, it is fair to assume that the majority of people want to reach their objective safely and efficiently, with different factors having different priorities. Microscopic approaches attempt to model the behavior of agents relative to other agents in their vicinity. In their work on Social Force Models (SFMs), Helbing and Molnár [2] reasonably suggest that typical pedestrians would like to take the shortest path to their destination, traversing the environment at some preferred velocity while maintaining their distance from other pedestrians, as in, they want to maintain some personal space. This simple agent modelling leads to macroscopic behavior that we observe in the world, such as pedestrians moving in groups or streams of people with similar velocity, while leaving room for streams of agents with opposing velocity so as to avoid collisions or having to constantly adjust their path planning. These are some sort of *soft rules*, or cooperative behaviors, guiding dynamic agents when navigating an environment; they are not legal restrictions, simply a form of more or less conscious teamwork which makes navigation easier for all participating agents. A better understanding of these behavioral patterns therefore seems important to achieve smooth robotic navigation that does not inconvenience others.

On the other hand, human agents have a general understanding that, in some areas, these soft rules are likely to break down, and we naturally exercise more caution there: places such as crossroads or building entrances necessarily have more chaotic traffic and agents become naturally more cautious. Microscopic models like SFMs do not account for this type of behavior, which is entirely based on the macroscopic setting, that is, the environment in which the navigation takes place. As such, we hypothesize that agent behavior is highly correlated with the layout of the environment. With many factors at play, from the physical layout to the high level context of the environment, it is difficult to predict behavior in complex environments using a simple agent models. The alternative, inferring behavior through data of pedestrian navigating the specific environment, may prove to be a better approach to understanding dynamic agent behavior.

In order to support this stream of research, we present a dataset of tracked agents in the 2017 Tsukuba Challenge environment as the main contribution of this work. Given the ability to revisit the environment, we created a detailed 3D occupancy map from point cloud data, rep-

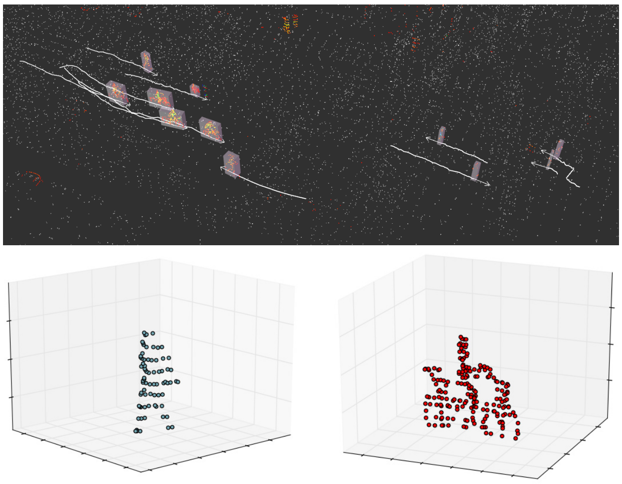


Fig. 2. Tracker output (top) at the Tsukuba Challenge. Dynamic objects are detected, with estimated bounding boxes and trajectory shown in white. Below, we show extracted, segmented pointclouds of a pedestrian (left) and cyclist (right).

resenting the static objects in the environment. This enabled us to localize in the environment and remove the static background from point cloud data, in turn allowing us to reliably detect and track dynamic objects. We release this dataset publicly[1] and provide some tools to analyse and visualize the data, for the convenience of the research community. Specifically, in this dataset we compiled more than 8 hours of data, traversing a distance of over 30 km and extracting nearly 10,000 dynamic object trajectories, mainly of pedestrians but also cyclists, competing robots and other dynamic objects. As shown in **Fig. 2**, we segment the object every frame that we track it, obtaining simultaneous detection and tracking information. To summarize the contributions of this dataset, its purpose is first for analysis of pedestrian behavior, most related to prior pedestrian crowd modelling research [3, 4]. Unlike this prior research, our dataset can be used to analyse more than microscopic (pedestrian-to-pedestrian) behavior; the large scale of the environment and provided map is intended to be used in order to analyse macroscopic (environment-based) pedestrian behavior, which is the main objective of the dataset. Then, since we also provide a large amount of tracked and segmented objects localised in a map, this dataset can also be used for testing detection, tracking and navigation algorithm. As an additional contribution, we perform a preliminary analysis of the data, discuss visible trends and propose some applications.

This paper is structured as follows. First, we will discuss related research in Section 2, reviewing the landscape of public datasets and discussing other relevant work. An explanation of the method used for creating the dataset follows in Section 3 as well as the data sanitization process in Section 4.2. Then, we give a description of the open-source dataset in Section 4 followed by a preliminary analysis of the data in Section 5 with a discussion of potential applications.

1. Filtered and raw data, processing tools and other scripts used in this work are available at https://github.com/MAVRG/meidai-data-tools [Accessed July 30, 2018]

2. Related Work

In this section, we review some of the currently available open-source dataset with pedestrian data. There is a large quantity of such dataset available; we will focus on the most popular dataset in computer vision and robotics as well as other dataset with similar objectives as ours.

Though there exist many dataset featuring pedestrian data, pedestrian *trajectory* data is scarcely available in the open-source community. The more prevalent publicly available dataset is without a doubt the KITTI Vision Benchmarking Suite by Geiger et al. [5]. While being largely focused on comparing vision-based detection and tracking algorithms utilizing camera images, lidar points were also logged during data collection. By projecting bounding boxes to the lidar frame, bounding boxes for point clouds were made available for the portion of the point cloud overlapping with the camera image. This labelled data represents a small subset of available lidar data, but the KITTI dataset is still the most widely utilized benchmarking tool even for lidar-based tasks. For our application, actual trajectories would have to be inferred from detection and tracking results. Furthermore, for this task, detection and tracking are done in image coordinates, but for behavior analysis, a global coordinate for all available tracking information is more practical; for most of the data available, the data collection platform (car) is moving, so pedestrian tracks are short and only a few tracks are seen simultaneously, making this dataset of limited applicability for our application. Nevertheless, we acknowledge that with all the data provided in the KITTI dataset, including egomotion information, GPS and calibration parameters for each sensor, it could be possible to reconstruct the pedestrian trajectories in a global frame with considerable work.

Otherwise, there are several camera-based datasets of pedestrian data as shown in **Table 1**. While some newer datasets such as CityScapes [6] have outstanding pixel-based segmentation of objects, the datasets are particularly tailored for benchmarking detection algorithms. Some have discontinuous data [6, 7] making tracking impossible, while others lack egomotion [8, 9], information which makes object trajectories available in local coordinates only. None of the datasets provide a map of the environment during data collection. In some cases, egomotion or GPS information is available which could make map reconstruction possible, but this would be difficult using forward facing cameras only. As previously mentioned, only with KITTI's camera and point cloud data would it be possible to reconstruct a map of the environment specifically when data collection occurred. By contrast, we provide a 3D point cloud map constructed precisely during data collection.

Table 1. Comparison of various dataset with labelled pedestrian data. Under description, we note the main purpose of the dataset, the quantity of segmented data as well as the type of objects (obj.). Under sensing, we underline the exteroceptive data provided in the dataset. Finally, under data, we characterize the information available in the dataset: Bounding Boxes (B.B.), Segmentated labels (pixels or point clouds) and Egomotion (Ego.) such as incremental or global localization information of the data collection platform (N/A if point of view is stationary), object trajectory information (Tracks). Finally we indicate if a map is included, as in a background map of the static environment serving as global coordinate frame consistent for all the data.

	Description			Sensing		Data				
	Purpose	Annotated Data	Obj. Type	Camera	Lidar	B.B.	Seg.	Ego.	Tracks	Map
Cityscapes [6]	Semantic Seg.	25,000 frames in 50 cities	50 classes	Mono	–	No	Yes	Yes	No	No
Daimler [7]	Path Prediction	64 trajectories	Pedestrians	Stereo	–	Yes	No	N/A	Yes	No
CamVids [8]	Semantic Seg.	700 frames, 345 unique obj.	32 classes	Mono	–	No	Yes	No	No	No
Penn-Fudan [9]	Detection	175 frames	Pedestrians	Mono	–	Yes	Yes	No	N/A	No
MIT tracks [3]	Behavior	40,453 tracks	pedestrians	Mono	–	No	No	N/A	No	No
Walking Paths [4]	Behavior	12,684 tracks	pedestrians	Mono	–	No	No	N/A	Yes	No
CalTech [10]	Detection	250,000 frames, 2300 unique obj.	Pedestrians	Mono	–	Yes	No	Yes	No	No
KITTI [5]	Tracking	50 sequences	Ped., cars	Stereo	HDL-64	Yes	No	Yes	Yes	No
KITTI [5]	Detection	80,000 frames	Ped., car, cyclist	Stereo	HDL-64	Yes	No	Yes	Yes	No
Stanford [11]	Detection	2400 object tracks	Ped., car, cyclist	–	HDL-64	No	Yes	Yes	No	No
Sydney [12]	Recognition	631 frames	13 classes	–	HDL-64	No	Yes	No	No	No
Ours	**Behavior**	**9,600 tracks**	**Ped., cyclists**	**Mono**	**HDL-32**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**

In summary, detection benchmarking datasets that dominate the landscape of publicly available data in robotics are unfortunately not well-suited to behavior understanding. Some datasets, such as the MIT Trajectory Dataset [3] or the Pedestrian Walking Path Dataset [4] were created specifically for the purpose of studying pedestrian behavior. Both datasets were collected by a single stationary camera overlooking a scene, which makes all pedestrian trajectories trivially in the same frame. However, this limits the size of the dataset; in the MIT tracks dataset, the data is collected in a small parking lot, while the Pedestrian Walking Path Dataset camera overlooks one room in the New York Grand Central station. The resulting research focuses therefore on microscopic interactions by modeling agents [13], as was the case with SFMs. With our dataset of pedestrian trajectories in a much larger scale environment, both microscopic and macroscopic behavioral analysis becomes possible.

There are only a few 3D lidar-based datasets currently available. The Sydney Urban Objects Dataset [12] and the Stanford Object Tracks dataset [11] are slightly older datasets which feature cropped point cloud of objects in urban settings, such as cars and pedestrians. The latter is particularly interesting because it features cropped object tracks, that is, a stream of lidar points corresponding to the same object, similar to what we are proposing. However, those objects are not localized inside map, nor related by some global coordinate frame, making this dataset unsuitable for our research objectives.

As such, the dataset proposed in this work would be the first lidar-based dataset of localized dynamic objects, making it very useful for the research community, in particular Tsukuba Challenge participants, giving insight on pedestrian behavior in a real-world environment. This dataset also has all the tools necessary to make it applicable for detection, segmentation, tracking and prediction research.

3. Dynamic Object Tracking

This section outlines the dynamic object tracking pipeline, which consists of three distinct operations on each point cloud supplied by the sensor: background removal, clustering (detection) and tracking. However, to perform background removal, we must first create a map of the environment. Another requirement of this pipeline is to be able to localize the robot within the map. The complete detection and tracking pipeline can be seen in **Fig. 3**.

3.1. Map-Making and Localization

To use this tracker, it is necessary to solve for the robot's egomotion. For localization, we use Autoware's[2] Normal Distributions Transform (NDT) mapping [14] and localization module [15] augmented by odometry data [16] which creates a point cloud map of the environment and localizes within it through scan-matching. With the ability to localize, we then use multiple dataset collected in the environment to create a probabilistic 3D occupancy grid map (voxel grid) of the environment using Octomap [17]. Using multiple dataset obtained at different times allows to filter out objects that are not part of the background, but appeared static in one or more data logs. **Fig. 4** shows the occupancy grid map created for background removal.

3.2. Background Removal and Clustering

With a background map, we can now start to detect and track objects within the map. For every scan, we localize the vehicle in the map, perform ground removal [18], then compare the scan with the background map: points that fall within occupied voxels of the background map are removed. While there often remains *background* points due to lidar noise or localization error, these are usually too few and far between to be significant.

2. https://github.com/CPFL/Autoware [Accessed July 30, 2018]

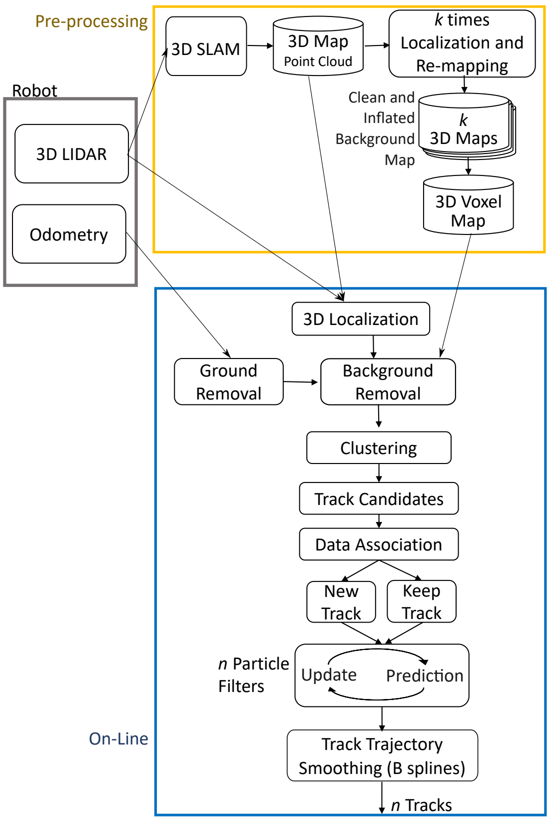


Fig. 3. Work flow of the dynamic object tracker. Both odometry and 3D lidar information is used from the robot. First using k data-collection runs in the environment, two maps of the static background are created, one for localization and one for background removal. After this pre-processing, we can localize, remove the static background, cluster the remaining points to detect and finally track a large number of dynamic objects on-line.

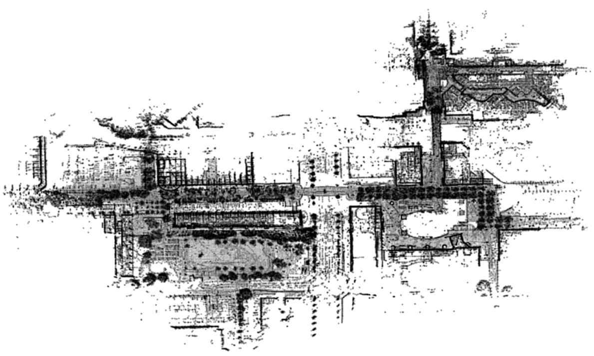


Fig. 4. Top view of the voxel grid map created of the Tsukuba Challenge environment using Octomap.

The remaining points are clustered through PCL's Euclidean Cluster Extraction[3] [19]. Their algorithm clusters points according to whether they meet some set distance threshold. We varied this threshold depending on (1) the distance of the points from the sensor and (2) if they are on the same or neighbouring lidar ring (from the same laser), to better account for the sparsity of points in regions further from the sensor. Then, we use a height filter to remove groups that are either too small or too big to be attributed to relevant dynamic objects – we keep clusters that are between 80 cm and 200 cm tall.

Unfortunately, for pedestrian tracking, this is often insufficient when it comes to groups of people walking close together. An overly strict threshold will sometimes over-segment one person into multiple tracking targets while a more lenient threshold may sometimes cause under-segmentation. To solve this problem, use a slightly lenient threshold and then further segment using a sub-clustering technique based on height, also from PCL. The algorithm examines the distribution of point cloud heights and looks for local height maxima. When there are two clear local maxima approximately shoulder width apart ($\approx$ 40 cm), there are likely two or more people. We therefore iteratively sub-cluster the point cloud until there is only one clear maxima. The clustering result before and after sub-clustering can be seen in **Fig. 5**.

3.3. Data Association

An important step in obtaining pedestrian trajectories is data association between observations over time, to determine which observations belong to the same track. At each time step, we compute a score-based likelihood to reflect how likely each new observation (point cloud cluster) belongs to some track. Then, we use Munkres assignment algorithm [20] to pair observations to tracks, maximizing the scores. The score is based on three elements:

1. Nearest Neighbour Score: euclidean distance between centroids,
2. Velocity Score: distance between observed centroid and predicted centroid based on current velocity, and
3. Shape Score: average Hausdorff distance between the new observation and last observation of the track [21].

3.4. Particle Filtering

Each detected objects is tracked in real-time using its own particle filter. Each observation that is not assigned to any track during data association is a potential candidate for tracking and is initialized with a new particle filter centred at the observation's centroid. Accordingly, tracks that have not been paired with any observations for more than five time steps are retired. Each track has a state estimated from its particles that comprises 2D position, heading, and speed. Particles are weighted according to the distance between the particle's position and the new observation's centroid, and resampled and normalized at each time step. During sampling, we assume constant velocity and use a Gaussian distribution. Particles with weights less than the minimal weight it would receive if all particles were equally weighted, are discarded and replaced by a new particle initialized at the track's estimated position. Particle clouds associated with tracked objects are shown in **Fig. 6**.

3. Available at: http://pointclouds.org/ [Accessed July 30, 2018]

3.5. Trajectory Smoothing

Since the output of the particle filter tracking is discrete points, it is useful to apply spline approximation to obtain a smooth estimate of trajectory. We use Scipy's[4] cubic b-splines [22] off-line on the output from the particle filter tracking, as well as on-line to extrapolate the track's future position to obtain heading, based on up to 50 of the track's previous estimated positions. When there are fewer than the necessary four data points for spline extrapolation, we assume constant velocity and infer heading from the track's velocity.

An example of the tracker output is shown in **Fig. 2**. From this figure, we can see that some background noise remains and but not clustered into objects, as they do not fit aforementioned criteria. Occasionally, static background can be clustered and considered a dynamic objects for a short period of time. To deal with this, we implement a filter for false positives, as explained in Section 4.2.

4. Dataset

In this section, we present the Meidai Autonomous Driving (MAD) Team Tsukuba Challenge Dynamic Object Tracks dataset, which features point cloud data of tracked dynamic objects collected in the Tsukuba Challenge environment shown in **Fig. 1**. We first show the data collection platform in Section 4.1, then discuss how the raw data is noisy and must be sanitized, in Section 4.2. Finally, present the dataset after post-processing in Section 4.3.

4.1. Robot

The dataset was collected with the platform shown in **Fig. 7**. It is a manually operated data collection platform, with a complete sensor suite: PointGrey Flea3 camera, Velodyne HDL-32 3D lidar, Hokuyo UTM30-LX 2D lidar and Xsens MTi-300 inertial motion unit. We also have motors attached to the wheels, purely for the attached encoders providing us with wheel odometry. We record all sensor information during data collection, but in this work we only ever use the 3D lidar and wheel odometry. As previously mentioned, robot egomotion is estimated through NDT scan matching [14] supplemented by odometry [16], to localize the robot inside the map.

4.2. Post-Processing

As discussed in Section 3, due to sensor noise and new static objects, the background removal is far from perfect. As such, static background is often picked up as objects and tracked for a short period of time, with objects naturally having have near-zero velocity. However, they tend to have erratic heading as, without any motion, the particle filter cannot accurately weigh different headings. Our dataset is littered with these false positives which must be removed for proper analysis of pedestrian behavior. We therefore look at the statistics of different trajectories and filter the data that is likely due to static background.

Before filtering, the dataset had the following statistics, while the statistics post-filtering are shown in **Table 2**.

- Total number of trajectories: 40,129
- Average path length of trajectories: 5.20 m
- Average distance covered by trajectories: 3.78 m
- Average track length (time): 5.04 s
- Average speed: 1.25 m/s
- Average rotational speed: 1.88 rad/s

Looking at the histogram distribution for the above statistics, we can see that a large majority of the tracks are in fact due to noise. Many are very short, both in terms of distance and time, which is not particularly helpful for prediction. There are also a few long tracks, each being the robot operator's trajectory. Nearly 30% of tracks have near zero average speed, which is again likely due to static background. Average bike speed on public roads is around 4 m/s, and as the environment is a dense pedestrian area, it is likely that objects tracked with very high speeds are due to tracker error. Finally, we previously mentioned that static objects have erratic heading, so filtering high rotational velocity is also a good technique. Through trial and visualization, we evaluated the impact of several filters and found that trajectories are likely to correspond to background noise if:

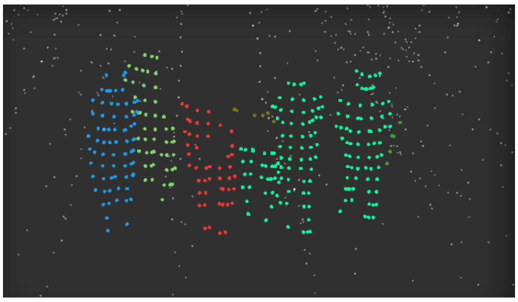
- path length was lower than 4 meters or greater than 100 meters – this would remove 68% of tracks,
- distance travelled was lower than 3 meters or greater than 100 meters – 70% of tracks,
- time tracked was lower than 2 seconds or greater than 60 seconds – 36% of tracks,
- average speed was lower than 0.2 m/s or greater than 6.0 m/s – 30% of tracks,
- average rotational velocity was greater than 3.0 rad/s – about 60% of observations.

The final values of the filter were largely determined by examining the results through visualization, but we can at least discuss the general idea.

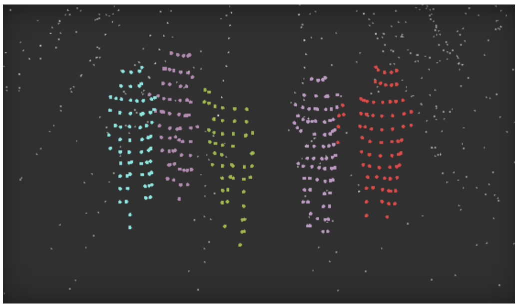
First, note we use two different metrics to measure path distance because we want to avoid two distinct scenarios. Path length measures the total distance travelled by a dynamic object, calculated by adding up incremental motion at each time step; if path length is very small then the object is essentially stationary and very likely static background, however we don't want to make the lower bound too large because short path lengths are possible especially for faster objects. On the other hand, detections due to background and lidar noise are usually unstable and the associated random error in tracking result can accumulate over time. Since this instability manifests

4. Available at: https://scipy.org/ [Accessed July 30, 2018]

(a) A cluster of pedestrians on the Tsukuba Challenge path.



(b) Output of the clustering algorithm. Note the three pedestrian on the right side of the image clustered together, one of which is heavily occluded.



(c) Output after iterative sub-clustering. We can see that the three clustered pedestrian were split up, with the occluded one no longer classified as a pedestrian due to small cluster size.

Fig. 5. Example of better pedestrian clustering results due to the head-based sub-clustering method used. Note that the colors are chosen randomly and seperately by the clustering and sub-clustering algorithms.

itself as a sort of rapid vibration of the object position, we can also filter by absolute distance travelled by the object, as in the difference between initial and final position. We threshold this slightly lower than path length to avoid filtering trajectories that largely feature rotations, for example a pedestrian walking around a corner. In both cases, we want to avoid tracking very long trajectories, since robot operators or Tsukuba Challenge officials are often tracked but not representative of normal pedestrian behavior.

Similarly, we threshold trajectories that are tracked for a very short time span because these are usually due to lidar noise or localization error, which makes background removal inaccurate. Again, dynamic objects tracked for a very long amount of time are rare and all due to operators,

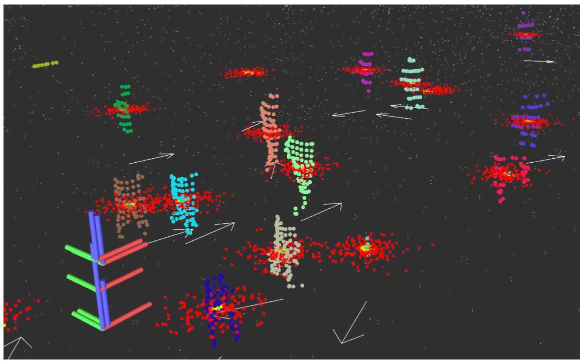


Fig. 6. Visualization of the 2D particle filter tracking of dynamic objects. Points associated with dynamic objects are given a random color per object. Filter particles are shown in a colour gradient according to their weight, largely low weights in red and highest weights in green. The red-blue-green axes shown represent the position of the various sensors on the robot.

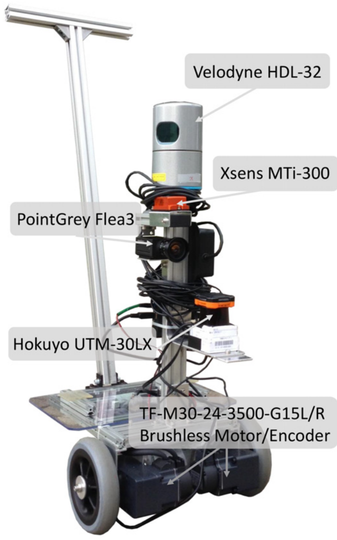


Fig. 7. The MinBot data collection platform and its sensor suite. Note we only use the Velodyne HDL-32 for detection and tracking. Also, only the motors' built-in encoders are used for additional robustness during localization and mapping.

Table 2. General information and statistics about the Tsukuba Challenge Dynamics Object Tracks dataset.

Duration of data collection	≈8 hours
Number of runs through the course	15 runs
Distance travelled during data collection	≈30 km
Number of dynamic object trajectories	9635
Number of segmented point clouds	≈500,000
Average duration of trajectories	10.56 s
Average trajectory length	12.65 m
Average velocity of objects	1.45 m/s

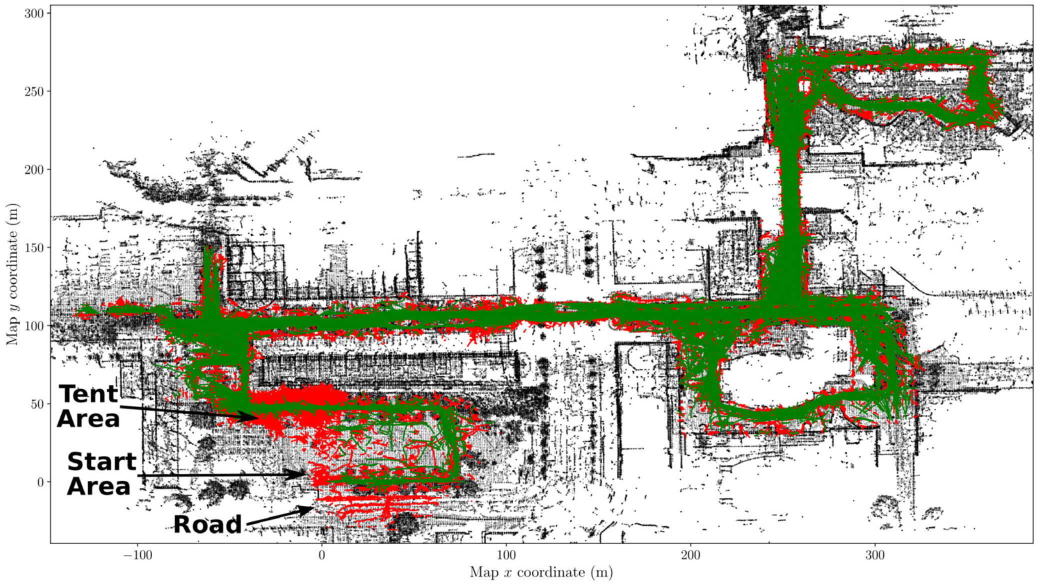


Fig. 8. Collection of good trajectories (green) and the ones filtered out (red). A large number of tracks are removed in the tent area and starting area of the challenge as they usually correspond to fairly static robot operators or background noise. The cars on the road also create several false positives, but these are also automatically filtered.

which are undesirable.

Then, we also filter trajectories based on their average absolute velocity (speed) and rotational velocity. We filter out very low speeds because those likely correspond to static objects. However, the statistic we are using is *average* speed and we don't want to filter out trajectories corresponding to pedestrians standing still for an important length of time; as such, we threshold the lower bound of absolute speed at 0.2 m/s to filter out near zero average speeds only. Then, Morales et al. [23] provides us with a good estimate of the preferred human walking speed, somewhere between 0.9 m/s and 1.4 m/s, and we expect bicycles to be significantly faster, which provides us an idea for an upper bound. We still want to filter very high speeds as those are usually due to cars, or poor tracking results caused by error in localization or data association, which changes the global position of a tracked object and gives it huge velocity. We chose a conservative upper bound of 6.0 m/s to definitely avoid filtering cyclists. Finally, we filter high rotational velocities as we have observed that background noise picked as objects usually have erratic heading, but don't filter low rotational speeds as this just indicates a straight trajectory which is not necessarily odd.

Cumulatively, these filters about 80% of the data, which represents a high rate of false positives. The dataset still contains nearly 10,000 trajectories after filtering, so while some potentially *good* trajectories may have been filtered due to strict thresholds, we have successfully retained more than enough data for analysis. In **Fig. 8**, we show the trajectories who pass all the filters in green, while the removed ones are in red. The quantity of data makes visualization difficult but the majority of red trajectories can be seen to coincide with buildings and other places that are not pedestrian areas. Glass buildings, as well as far away objects, tend to produce noisy data, explaining why background detection fails. The tent area, where teams prepared their robotics platform, as well as the start area for the challenge featured largely static or erratic trajectories. Other areas like roads, near the bottom of **Fig. 8**, lead to noise from vehicles which can be tracked for a few frames. As previously mentioned, cluster size is taken into consideration during detection so full cars are not often tracked, but given certain line of sight or the right occlusions, point clouds caused by cars can be mistaken to be a pedestrian or cyclist. However, the resulting tracks are obviously not pedestrian-like and were filtered through post-processing.

4.3. Sanitized Dataset

As the main contribution for this work, we provide a sanitized dataset of dynamic agent tracks. **Table 2** compiles some information and statistics concerning the dataset, after the filtering. In **Figs. 9–12**, we show the distribution of the aforementioned statistics on our dataset. Particularly in **Fig. 11**, we see a clear peak around the typical pedestrian velocity of 1.2 m/s.

The sanitized dataset provides the following information:

- *Map of the Tsukuba Environment*: 3D point cloud map and 2D occupancy grid map of the Tsukuba challenge environment.

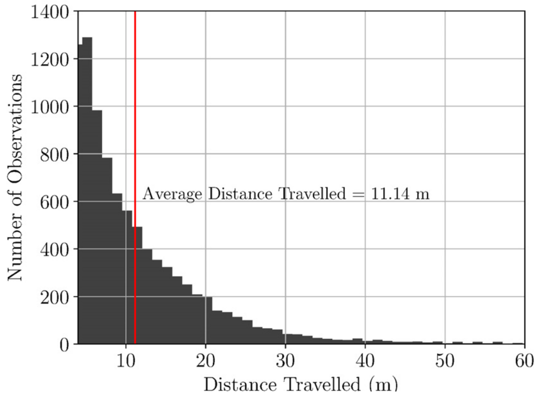


Fig. 9. Distribution of distance travelled (meters) after filtering trajectories with distance travelled lower than 3 meters and greater than 100 meters. The average distance travelled for the dataset after filtering is 11.14 meters.

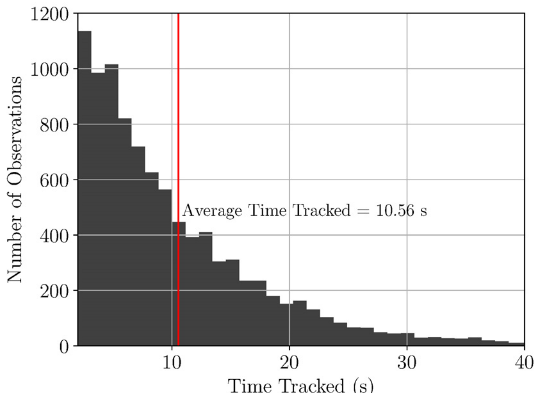


Fig. 10. Distribution of time tracked (seconds) after filtering trajectories tracked for less than 2 seconds or longer than 60 seconds. The average time tracked after filtering is 10.56 seconds.

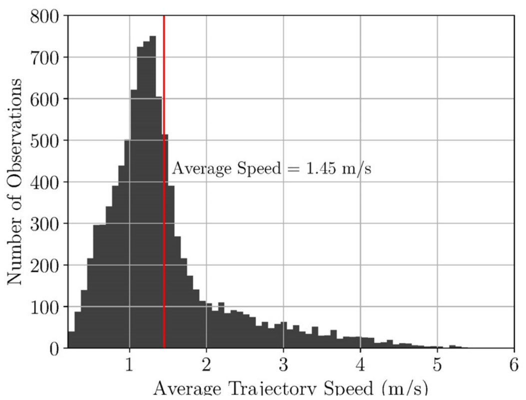


Fig. 11. Distribution of average speed (m/s) after filtering out trajectories with average speeds lower than 0.2 m/s or greater than 6.0 m/s. The average object speed in the dataset after filtering is 1.45 m/s.

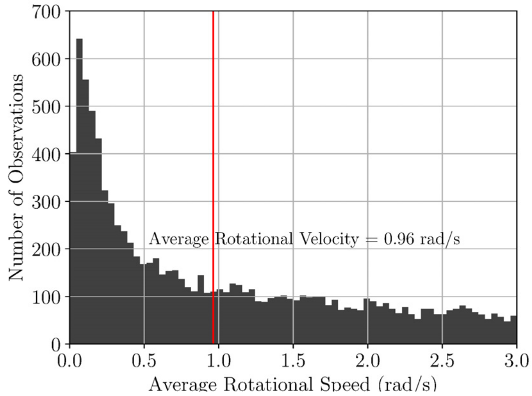


Fig. 12. Distribution of average absolute rotational velocity (rad/s) after filtering out trajectories with average rotational speeds higher than 3.0 rad/s. The average rotational speed after filtering is 0.96 rad/s.

- *Robot Trajectory*: position of the robot inside the map at each timestamp.
- *Dynamic Object Locations*: 2D and 3D locations of dynamic objects, with object ID and timestamp, localized in a global coordinate frame.
- *2D Smoothed Trajectories*: b-spline-derived smooth trajectories.
- *Velocity and Heading*: derived velocity and heading from the smooth trajectory for each dynamic objects.
- *Bounding Box*: 3D bounding boxes and centroid location of each object, and
- *Object Point Clouds*: 3D points inside each objects bounding box.

We also provide sample code for extracting the data and visualizing the trajectories and point clouds.

5. Discussion

In this section, we show some visualizations of the data provided in the Tsukuba Challenge Dynamic Tracks Dataset and provide some preliminary analysis based on the distribution of absolute velocity, then heading.

5.1. Absolute Velocity

Figure 8 shows the difficulty with visualization of trajectories. A better approach is to color each trajectory based on the absolute velocity. In **Fig. 13** we see the entire dataset of trajectories colored by speed. The scale of the map still makes it difficult to see any patterns, and trajectories are overlapping with each other, but we can at least see that faster trajectories are far more prevalent in some areas of the map, namely the larger main roads. To get a better understanding of the data, we will focus on

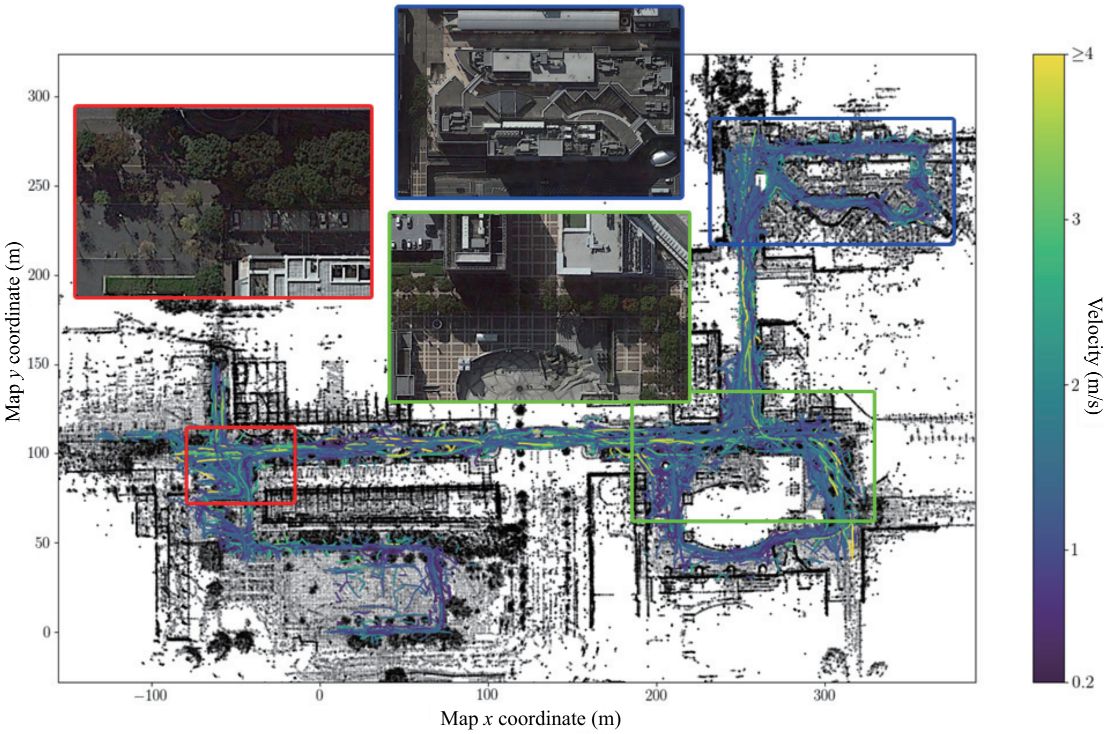


Fig. 13. Plot of all trajectories in the dataset, colored by average speed of the tracked object. At this scale, it is difficult to analyze the data, but we can discern areas where almost exclusively used by pedestrians due to the absence of fast, yellow trajectories. For a clearer analysis, we focus on three areas, the first in red, second in green and third in blue, with top down images of each area provided with a color-coded border.

three smaller zones. Zone 1 is the first major intersection of challenge which robots pass by multiple times, labelled in red in **Fig. 13**. It connects the main pedestrian road to Tsukuba Capio Cultural Center, the Dayz Town Shopping Center and several connected streets. Zone 2, labelled in green, is a large open space at the intersection of a shopping area with many businesses and shops, and the two main streets in the challenge, perpendicular to the each other. Zone 3, labelled in blue, is a narrow shopping strip with an indoor section on the right hand side. For each one, we provide two separate figures, one displaying the trajectories colored by velocity on the left, and colored by heading on the right.

Looking more closely at the speed distributions in the three zones, we can definitely see that only some areas can be navigated quickly by bicycles, or some other motorized vehicles. Note higher speeds are associated with brighter colors, with 3.0 m/s shown in bright green and 4.0 m/s and above shown in yellow, in the left-hand side figures. In **Fig. 14**, it is clear that the two walkways leading to the Tsukuba Capio Cultural Center, labelled (A) and (B), are not convenient for rapid navigation by bicycles and that obstacles tend to be slower in this area. In **Fig. 15**, we can see the intersection is well-suited for rapid navigation, with the exception of the shopping area in the bottom left, labelled (A), which narrows and forces slower navigation. In the third zone, shown in **Fig. 16**, the narrow shopping area is definitely unsuitable for fast navigation, as all trajectories in this area are about pedestrian walking speed. However, the main road at the entrance of the shopping area, marked with (D), does have some faster moving objects. Knowing where we can expect fast moving obstacles could perhaps be very useful for safer navigation. For example, we can design our planner to decrease the robot velocity significantly when transitioning between an area with slower average navigational speeds, to an area with potentially fast obstacles.

5.2. Heading

In the heading plots on the right-hand side, we focus on the direction of the trajectories to get a better understanding of the network of pedestrian tracks. The first zone in **Fig. 14** is clearly a complex intersection, with different roads being perpendicular to each other. The bulk of the traffic is on the main horizontal road, but the pedestrians going from the Tsukuba Capio, labelled (A) and (B), to the pedestrians walkway labelled (C) cut through the main road diagonally and could potentially cause dangerous situation. However, near the center of the zone, in the area labelled (D), pedestrian motion is not particularly constrained nor dense, so we can understand this to be an open space that is not so often used. As an example of how this data could influence our planning, perhaps our robots could navigate freely towards this open space to

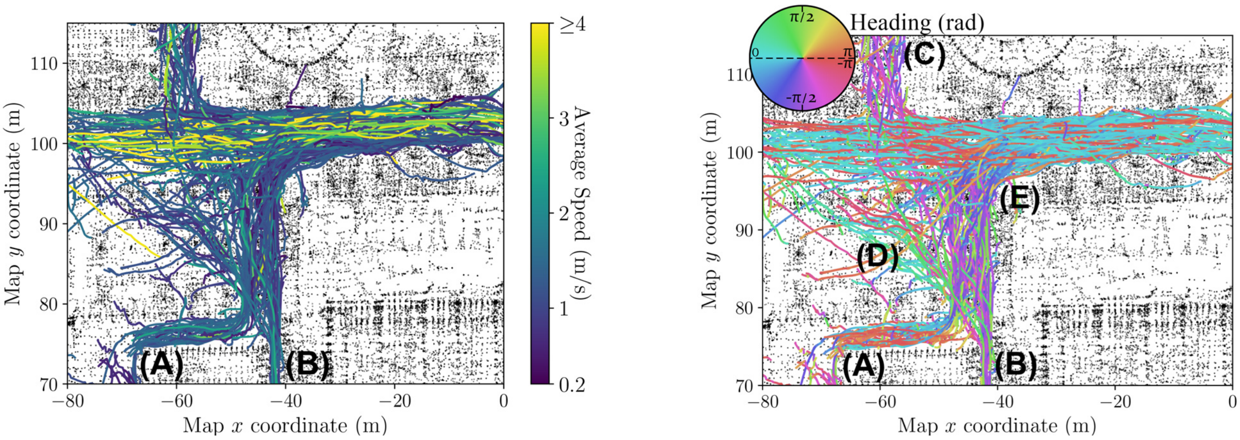


Fig. 14. Zone 1 labelled in red in **Fig. 13**, trajectories colored by velocity on the left and colored by heading on the right. Walkways marked (A) and (B) lead to the Tsukuba Capio Cultural Center.

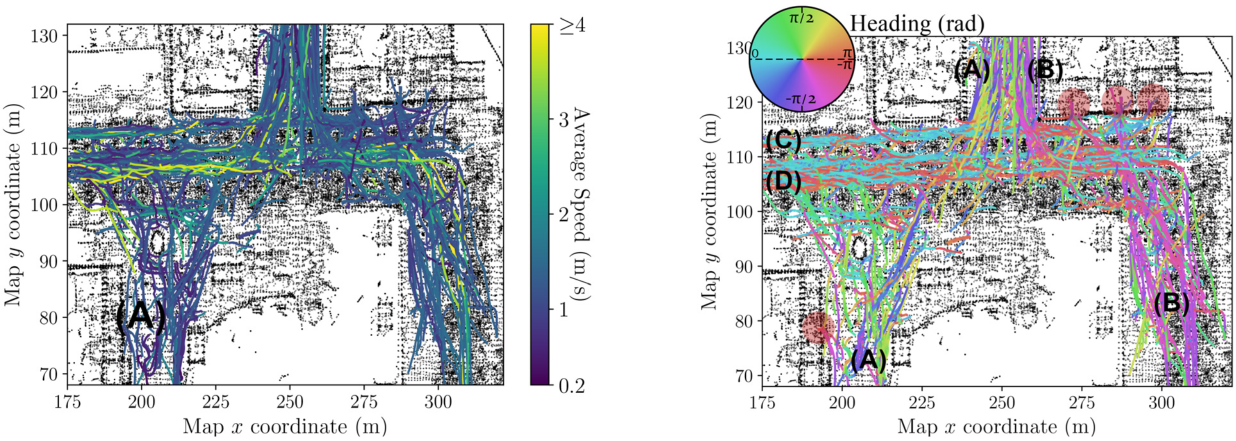


Fig. 15. Zone 2 labelled in green in **Fig. 13**, trajectories colored by velocity on the left and colored by heading on the right. It is the main intersection navigated multiple times during the challenge and has multiple stores and points of interests. The various hotspots as determined by the data, particularly popular store entrances, are labelled in red.

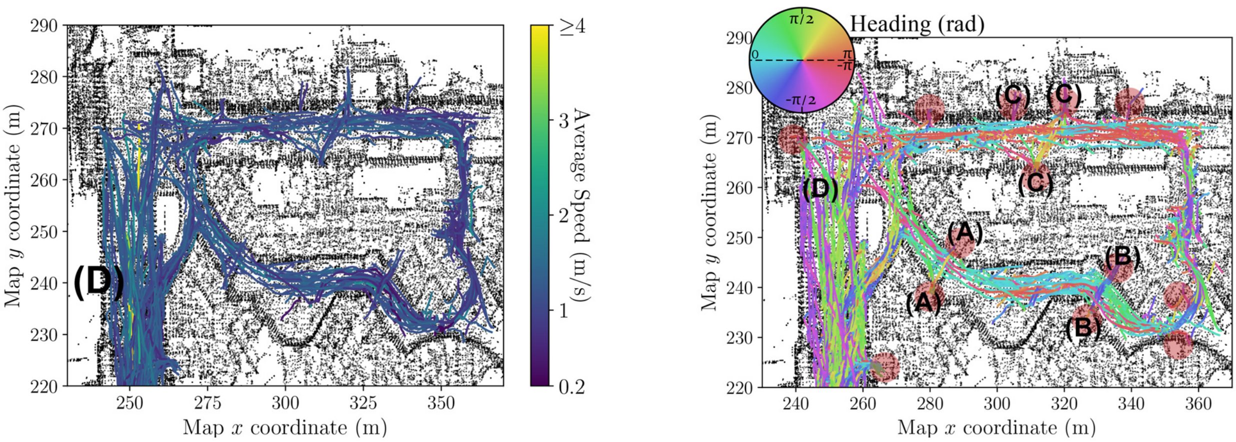


Fig. 16. Zone 3 labelled in blue in **Fig. 13**, trajectories colored by velocity on the left and colored by heading on the right. It is largely a narrow shopping strip with an indoor section. Various hotspots as determined by the data, particularly popular store entrances, are labelled in transparent red.

first survey the scene, before engaging in the dangerous intersection. This may be a safer alternative than making the tight right turn with limited visibility, near the area labelled (E).

The second area, shown in **Fig. 15** is the other major intersection in the Tsukuba Challenge, which robots have to pass through three times. The heading plot definitely motivates us to try and estimate pedestrian networks from this data; while this area is very wide and open, there seems to be some clear preferred routes by pedestrians. First, note the very clustered, dark blue trajectories as well as the yellow trajectories connecting the two areas labelled (A). An almost mirrored pattern can be seen in purple and green on the other side, with trajectories connecting the two areas labelled (B). Furthermore, the narrow side-walk on the top side of the main path, labelled (C), seems to be much more frequently used by pedestrians going to the left, with their trajectories in light blue. The pedestrians going to the right, shown in red, are more frequent on the lower side of that road, at the level labelled (D). These fairly clear patterns motivates us to perform a more robust, probabilistic analysis of these motion patterns as future work.

We can get some similar insight in third zone in **Fig. 16**. Interestingly, we can see that pedestrians seem to prefer navigating this looping shopping area in counter-clockwise fashion. Since this is opposite as the Tsukuba Challenge Course, we cannot attribute this to tracking other robot operators. However, we can clearly see streams of pedestrians disrupting this flow, as they move from shop to shop. Areas labelled (A) and (B) show how several pedestrian navigate between opposing stores, perpendicular to the main road. The situation labelled in (C) is more complicated, as there are three nearby store entrances again disrupting the flow of traffic. These represent some clear areas that warrant special caution during navigation, as pedestrians may emerge from stores and interfere with the robot without allowing much reaction time. Otherwise, just outside the shopping area in the area labelled (D), we can also see some preferred trajectory, based on heading.

Additionally, from this dataset, we can discern the entrances of various popular stores in the area, which is not obvious from the point cloud map alone. We note those with red circles on our heading maps in **Figs. 15** and **16**. We can potentially take this into consideration during navigation, avoiding these *hotspots* in the environment.

From this superficial, preliminary analysis, we believe some interesting research into macroscopic pedestrian behavior could be performed using this dataset. While we do not touch on it here, we also include the temporal relationship between tracks, so microscopic interactions between pedestrians could also be studied. Finally, we include segmented pointclouds for the each dynamic tracks, which can further lidar-based detection research as well as dynamic object modelling from lidar data.

6. Conclusion

Navigation in social environments poses unique challenges that go significantly beyond detection and tracking of dynamic objects. In order to be more socially conscious when planning our navigation in public environments, we need a better understanding of how pedestrians navigate specific environments. While previous work can predict some general behavior in simple environments, the situation is much more complex in real-world scenarios and using data driven methods to understanding pedestrian behavior is likely a better option in those circumstances. Unfortunately, the current research community does not have publicly available data that conveniently enables this avenue of research.

As such, the main contribution of this work is a sanitized dataset of tracked dynamic object in the environment of the 2017 Tsukuba Challenge. As this challenge is an annual event, it is an ideal test case for the long-term and large-scale behavioral analysis of dynamic agents, mainly pedestrians, in real-world settings. The dataset features nearly 10,000 trajectories of pedestrians, cyclists, robots and other types of slow-moving vehicles, all sharing this public space. The presence of several participants in the Tsukuba Challenge creates an environment where pedestrian are aware of the scarce but non-negligence presence autonomous vehicles and perhaps adjust their behavior accordingly. This event creates an environment which effectively represents a future where humans and machine share public space commonly. We reiterate that it is therefore essential to have a better understanding of macroscopic human navigation as well as microscopic interactions with robots. With this dataset and the tools we provide, we support research specifically on macroscopic pedestrian behavior, as well as the human-machine interaction element which makes these dense pedestrian environment so challenging for Tsukuba Challenge participants. As we provide bounding boxes and segmented point clouds, this dataset can additionally be used for traditional detection and tracking tasks.

As future work, we want to perform an in-depth analysis of the trajectory data to estimate probabilistic pedestrian road networks, which we plan to use to improve our tracking and planning algorithms. We also plan to manually label object classes and use it as training for lidar-based supervised detection algorithms. To assess the accuracy of the data collected, we also plan to conduct rigorous benchmarking of the detection and tracking pipeline to obtain an estimate of the accuracy and precision of the collected data.

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