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Implementation of Dynamic Boundary on Multiple Kalman Tracking Using Radar

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***Abstract*—The development of advanced driver assistance systems (ADAS) is of importance to prevent the potential driving risks on the road, which relies on the perceptive sensors to detect and identify the traffic conditions. This paper examines a method to track multiple objects and determine the high risk obstacles using radar. We experiment the scenarios as the vehicle and pedestrians in front, as well as the pedestrian crossing the street. The multiple tracks are achieved based on the Kalman filter. This work implements the state prediction model to compensate the missing targets, and the false positives are excluded through a threshold of bad tracks. To identify the potential obstacles, we impose two boundaries, i.e., lane and dynamic boundaries as the region of interest on the multiple tracks. It is demonstrated that the dynamic boundary benefits the finding of high risk obstacles and excludes most of the background noises. The lane boundary takes the advantage of tracking objects along the driving path: however, it could underestimate the risk of transverse moving objects in which the tracks are not continuous crossing the lanes.**

I. Introduction

With the increasing demand of driving safety and comfort, the development of Advanced Driver Assistance Systems (ADAS) attracts the high attention in recent years [1]. The ADAS application includes Autonomous Emergency Braking (AEB), Adaptive Cruise Control (ACC), Forward Collision Warning (FCW), etc. The systems strongly rely on the sensors such as monocular/stereo camera, radar, and LiDAR to perceive the surrounding traffic environment and to fuse the information from those sensors [2]. It has been studied over a decade regarding the data fusion architecture of multiple sensors [3] [4] [5]. The sensor fusion strategies can be classified into three main kinds depending on the fusion level, i.e., low-level, intermediate-level, and high-level fusion [6] [7]. The drawback and efficiency of different fusion paradigms are investigated and compared in [8].

The tracking issue is of major importance in the data fusion problem, particularly in the high level fusion (track to track fusion). In the track fusion, each sensor first performs the local tracks and then fuses all the information into a global tracking center [9] [10]. The challenges of tracking can be resulted from several reasons, e.g., the difficulty of object identification, the interference of background noise, and the loss of targets due to the sensor sensitivity. This study aims to develop a method that tracks the road obstacles efficiently. Of special interests are the tracking of single/multiple major objects. The perceptive sensor utilized here is a long range radar($77GHz$). It is known that radar is particularly noisy among all of the range-finder sensors: however, radar performs the best capability to detect the distant objects ($> 100m$), and is not vulnerable to the poor weather and light condition. This work mainly focuses on the object tracking using the radar since it could track the objects covered in the extensive distance and would play as an important part in the sensor fusion. A region of interest (ROI) is implemented in this paper because it is very difficult to extract the object feature based on the radar sensor.

This study implements the linear Kalman filter [11] as the major scheme on the tracking of multiple objects. This paper is organized as follows. The procedure of the tracking method is detailed in section 2. In section 3, we demonstrate the experimental scenarios and the tracking results. In combination with the selection of the lane boundary or dynamic region of interest (ROI), we present the the performance of the vehicle and pedestrian tracking, respectively. Finally, we give the discussion and conclusion in section 4.

II. Methods Statement

This study develops the multi-objects tracking method based on the linear Kalman filter. The Kalman filter equations are listed in Equations $(1) - (5)$, where A is the state transition matrix, B is the input control, P_k is the covariance matrix, H is the observational model, Q is the system noise, R is the observational noise, and K_k is the Kalman gain. The Kalman filter applies recursively, where $x_{k-1|k-1}$ is the best state at the time $k-1$, and $\hat{x}_{k|k-1}$ is the state estimation at the time k, which is estimated from the previous time step $k-1$. In this work, we vary the value of observational noise R_k as the confidence of data measurements. w_k and v_k are white, zero-mean and uncorrelated noises. The covariance matrix P_k describes the uncertainty of the tracks. δt of matrix A is the sampling time. We neglect the control term B for the simplicity.

In the first step, we record all the information detected by the radar. The Kalman filter is implemented on all the measurement points, starting with multiple candidate targets. Note that the targets might disappear in some frames due the sensor sensitivity. A distance threshold is applied to estimate whether the focused target is continuing or disappearing in the time sequence. The target is tracked in every time frame, and the prediction model will compensate the missing experimental data if the one is lost in the next frame. Such

TABLE I
SPECIFICATION OF THE RADAR SENSOR

range	FOV	sampling frequency
$\sim 60m$, $\sim 200m$	$\pm 28°$, $\pm 17°$	66 ms

the experimental data compensation is likely considered as a bad tracking point. We continue track the bad tracking point if the observational data is present again in the next 2 or 3 frames. Otherwise, the bad tracking will be terminated after several tracking iterations. Meanwhile, the new tracks are also recorded in every time frame.

In our strategy, the objects inside the field of view (FOV) will be all included. It is well known that radar is difficult to identify the type of objects. To find out the potential high risks on the road, we define the size of ROI to exclude the tracks that are not highly concerned. In section 3, we demonstrate the results of using two types of boundaries, i.e., lane boundary and dynamic boundary. The cases of vehicle, single pedestrian, and multiple pedestrians will be estimated.

$$\hat{x}_{k|k-1} = Ax_{k-1|k-1} + Bu_{k-1} \tag{1}$$

$$P_{k|k-1} = AP_{k-1|k-1}A^T + Q_k \tag{2}$$

$$K_k = P_{k|k-1}H^T(HP_{k|k-1}H^T + R_k)^{-1} \tag{3}$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k(z_k - H\hat{x}_{k|k-1}) \tag{4}$$

$$P_{k|k} = (I - K_kH)P_{k|k-1} \tag{5}$$

$$A = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \delta t & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & \delta t \end{bmatrix}, H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \tag{6}$$

$$w_k \sim (0, Q_k), v_k \sim (0, R_k), \tag{7}$$

$$E[w_k w_j^T] = Q_k \delta_{k,j}, E[v_k v_j^T] = R_k \delta_{k,j} \tag{8}$$

III. RESULTS

A. Car to Car Rear Stationary (CCRs)

In this section, the tracking of a vehicle target is addressed. Figure 1 depicts the scenario of the experiment, where the host and target cars are initially at the different locations apart about $200m$. The target car kept stationary, and the host car was driving forward at a speed around $50kph$. As shown in Figure 1, the experimental space is wide but with the mountain behind. We mount the long range radar on the height around the bumper of the host car to detect the front obstacles. Table 1 lists the specification of the radar sensor.

While the host car was moving forward, the radar was receiving the information of the detected objects. Figure 2 illustrates the locations of front obstacles, where the dots indicate each possible target although it might include some false positives. We overlap the positions of all the detected targets into only one frame to describe the variation of the detected distance so that the time information is included but not shown here. It is presented that the target vehicle is detected from the beginning ($\sim 200m$) to the end ($\sim 9m$) of the driving. The background signals are very noisy and spread widely, particularly toward the end of the driving. This result is not unexpected because the behind mountain starts to be covered inside the radar FOV at later part of the driving. The blue lines of Figure 2 illustrate the FOV of the radar sensor.

Fig. 1. Scenario 1: CCRs experiment. The top panel illustrates the global view, while the bottom picture presents the side view. The rear one indicates the host car, and the front one represents the target car.

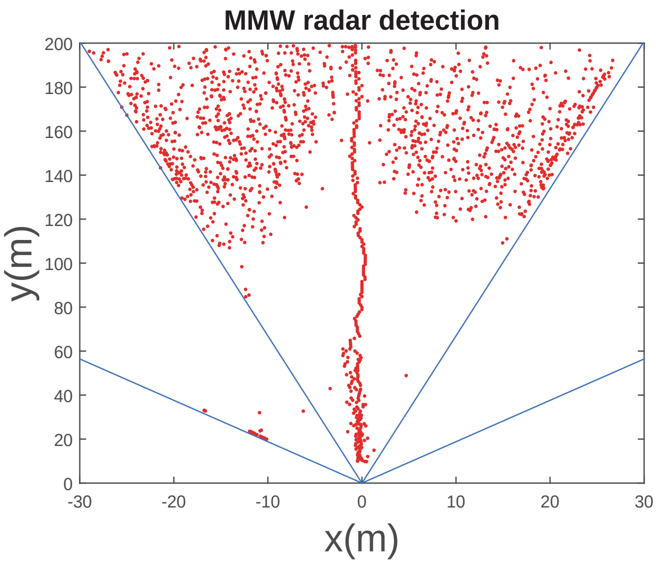

Fig. 2. MMW radar detection of CCRs scenario. The dots indicate the location of the front objects in the radar coordinate.

Figure 3 demonstrates the Kalman tracking results of multiple targets, which the circles represent the tracking position of the objects. The historical position of each track

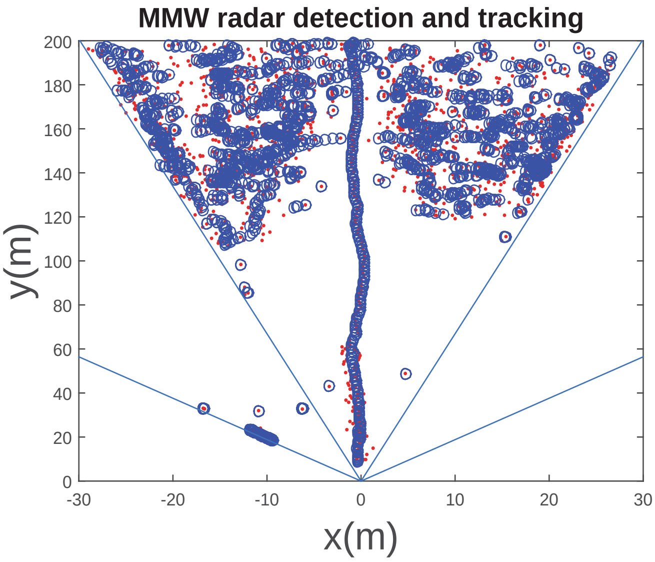

Fig. 3. MMW radar detection and Kalman tracking. The format is the same as Figure 2, except the circles represent the Kalman tracks.

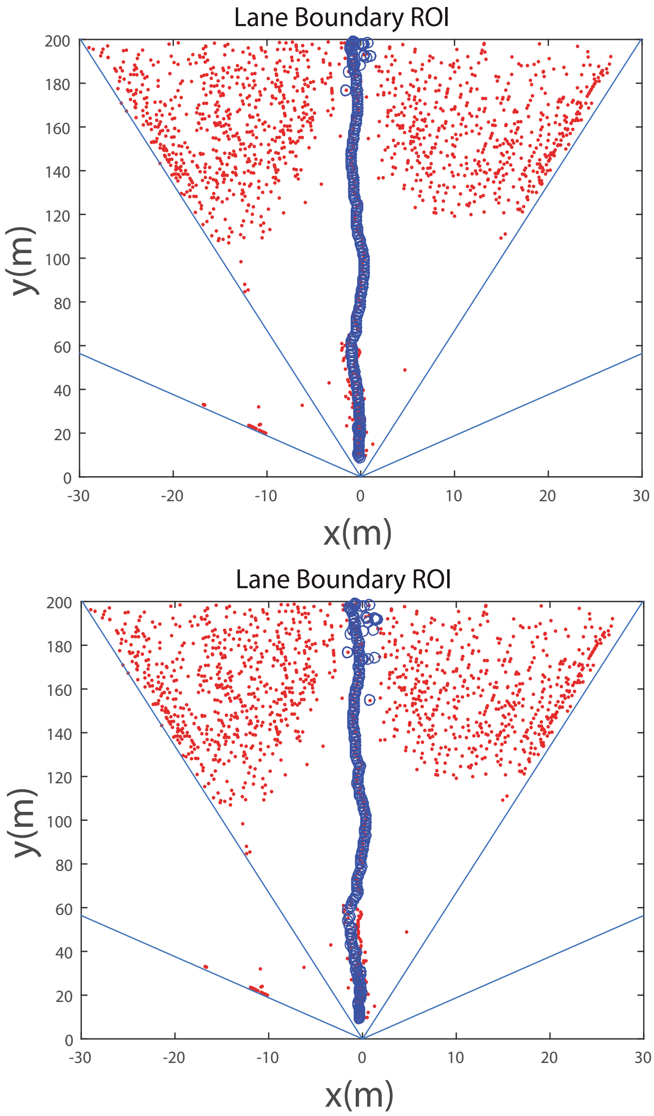

Fig. 4. Lane boundary application. The top (bottom) panel shows the results of using larger (smaller) observational noise R. The format is the same as Figure 3, except for the implementation of lane boundary.

is recorded and checked in every frame. We define the new track is presented if the point target appears beyond a certain threshold of distance in the next frame. If the focused target is lost, the state prediction model (Eq(1)) will be applied to compensate the absence experimental data. The bad tracking of the lost target is continuing traced, and the track number is counted after every iteration. The track of the bad tracking will be terminated after several cycles. It is presented that the target car is clearly tracked although the background is very noisy. In Figure 4, we will implement a lane boundary to exclude the background noises. The boundary limitation is considered as a distance threshold, which is checked after every iteration, thereby excluding the targets outside this region. Note that the "noises" here are not indeed the false positives. It could probably be the true objects that we just do not consider as the major road obstacles.

The results of the land boundary embodied are shown in Figure $4(a)$ and $4(b)$. To consider the track performance affected by the noise term in Kalman filter, we examines two cases in which the value of observational noise R is varied. The top panel implements the higher observational noise, while the bottom one shows the lower noise value. Figure 5 illustrates the vehicle tracking path at $y = 30 \sim 100m$. It is shown that the tracks are closer to the measurement in the lower R case. This result is not unexpected because the lower observational noise corresponds to the higher confidence of theoretical state prediction. It is somehow difficult to select the adequate value of the noise term, especially in the very noisy background. Overall, Figure 4 demonstrates that the application of lane boundary can exclude most of the low-risk objects. The target vehicle is tracked in the entire driving path.

The advantage of using the lane boundary is to specify the potential candidate of obstacles in the driving path. Here we emphasize that radar is the sensor with high range detection but limited object identification capability. Without the image sensor, the local radar tracking can only indicate the existence of possible obstacles on the way. In our tracking strategy, the false positives can be eliminated after several iterations of bad tracking. Only one lane boundary is implemented here so that a new question comes out: how about the detection of multiple obstacles located in the multiple lanes?

To deal with this problem, we try to apply the dynamic boundary instead of the uniform lane boundary. The selection of the boundary threshold is according to the position of the nearest detected targets. The threshold is dynamically adjusted depending on the distance of the selected one and enlarged linearly in the near part of the driving path. We also track the historical threshold value and adjust a new one if the threshold is abruptly varied. Figure 6 shows the result of the implementation of dynamic boundary. It is demonstrated

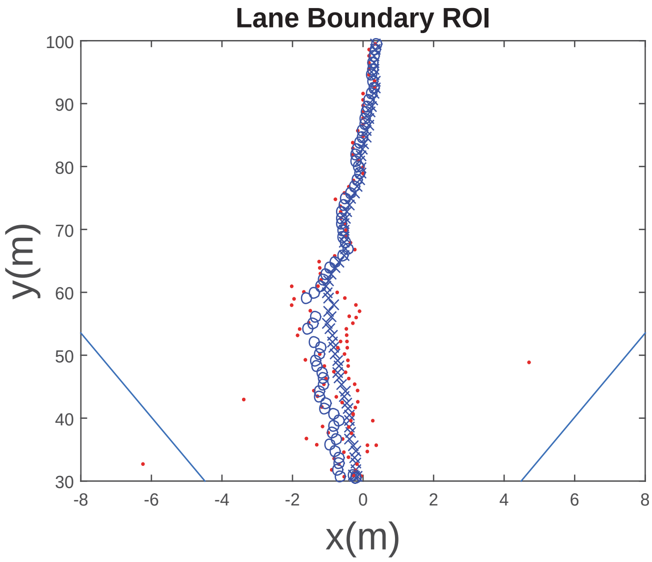

Fig. 5. Comparison (zoom-in) of the two panels in Figure 4. The cross (circle) corresponds to the case of larger (smaller) observational error.

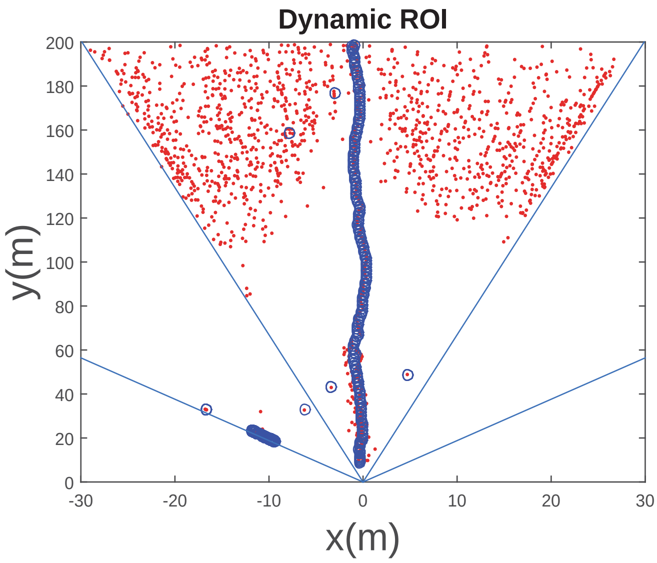

Fig. 6. Dynamic boundary implemented on the Kalman tracking. The format is the same as Figure 3.

that most of the low-risk tracks are excluded. Instead of specifying the width of the lane, we apply the dynamic distance boundary apart from the center of ego-vehicle. The result performs that the vehicle target is well detected along the driving way.

B. Pedestrian

In this section we present the performance of pedestrian tracking. Figure 7 illustrates the experimental setup in which the pedestrian was walking slowly across the street. The composition of the background is more complicated than in scenario 1. There are several vehicles behind so that the background is very noisy.

Figure 8 shows the location distribution of the detected targets. Again, we illustrate the positions of all the detected targets overlapped into only one radar frame to examine the entire tracking process of the walking pedestrian. As shown in Figure 8, the nearest horizontal line ($y =\sim 7m$) is composed of many dots, which corresponds to the location of the walking pedestrian. We notice that the pedestrian is not always be detected. The dot line of the pedestrian is not perfectly continuing (some samplings are missed). In the program such the target lost is compensated by the state prediction, which starts to count the number of the bad tracks. It stops the replenishment if the target appears again in the next frame.

Fig. 7. Scenario 2: A pedestrian crossing the street. Several vehicles are behind.

Figure 9 demonstrates the result of the pedestrian tracking. We implement the dynamic boundary on this case since the the real object was crossing different lanes. It is shown that the pedestrian is tracked (circles) in the process of walking. By applying the dynamic boundary, we identify the candidate obstacle that is of highest risk. We consider that those objects away from the observer are of less importance so that they could be ignored. In this case, we might underestimate the risk of the moving pedestrian if the lane boundary is imposed.

C. Multiple Pedestrians

We have demonstrated the tracking of single vehicle and pedestrian in the previous subsections. In this section, we present the case of multiple pedestrians tracking on the street. Figure 10 illustrates the setup of the experiment. There are two pedestrians in front of the observer. The pedestrians were walking slowly along the way, with a separated distance about one lane. The setup of the noisy background is the same as in the single pedestrian experiment (Scenario 2).

As the same format of Figure 9, Figure 11 shows the distribution of the detected target in this case. The two vertical lines are constructed from many time frames, which indicates the walking tracks of the pedestrians. Again, Figure 12 presents the nice tracks of multiple pedestrians. Toward the end of the tracking, the corner of the background building was detected and covered in our interest region. Note that the circles were apart from the pedestrians and the number of bad

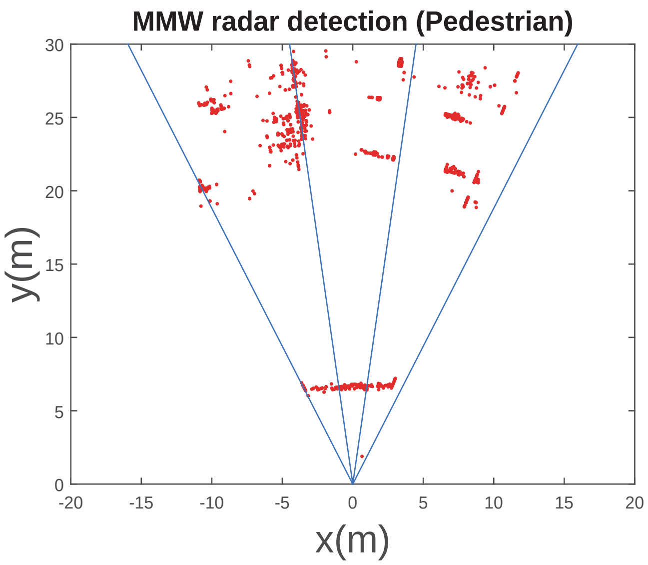

Fig. 8. MMW radar detection of the pedestrian.

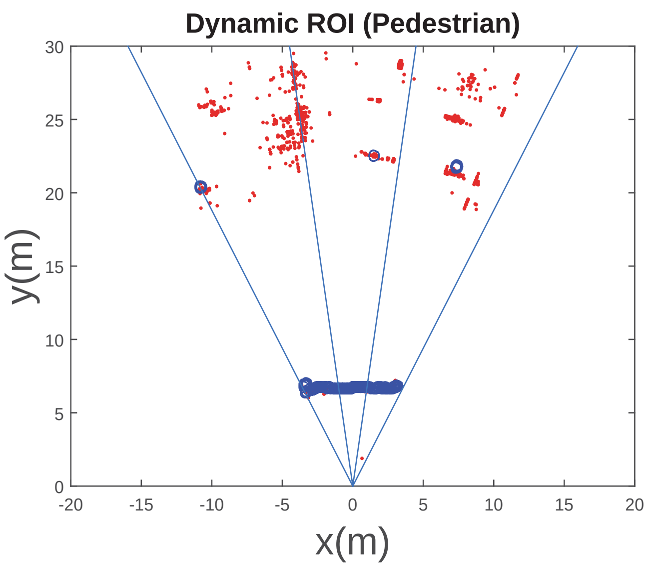

Fig. 9. The format is the same as Figure 6 except for the pedestrian crossing scenario.

Fig. 10. Scenario 3: Multiple pedestrians walking along the street.

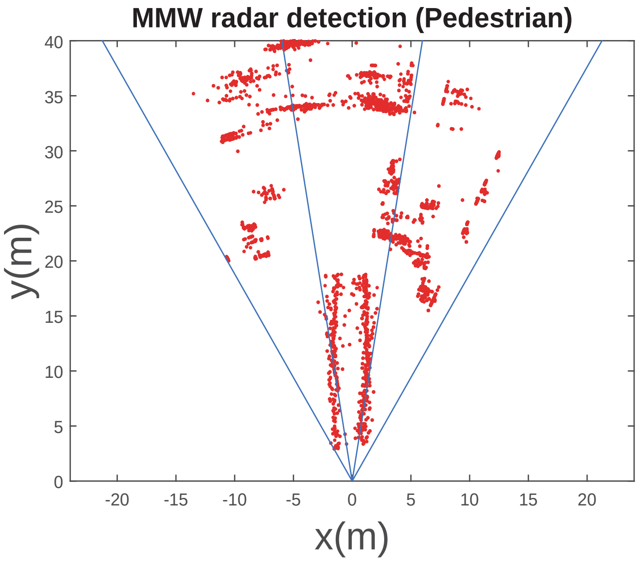

Fig. 11. MMW radar detection of multiple pedestrians walking scenario.

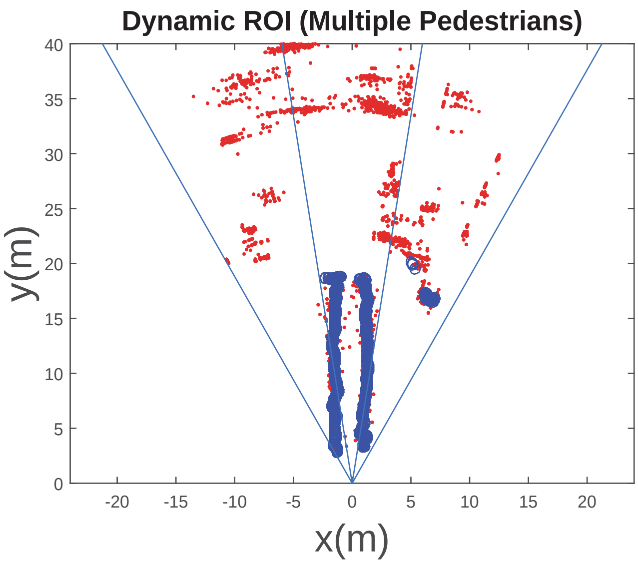

Fig. 12. The format is the same as Figure 9, except for the multiple pedestrians walking scenario.

tracking is not over a certain threshold. Such the result means that the circles can represent an real object although it is not our main concern. We strengthen that radar does not have the capability to distinguish the type of real objects from the noisy background.

IV. Discussion and Conclusion

This study presents a method to track and identify the potential high risk obstacles using radar sensor. We implement the Kalman filter on the detected objects and perform the tracking results of vehicle, single pedestrian and multiple pedestrians. To track the multiple objects, all the historical tracks are recorded and checked as the continuing or disappearing targets. Meanwhile, the track of new target is also defined using a threshold of certain distance. It utilizes the state prediction model to compensate the lost target, which the bad tracks are terminated after several iterations. To identify the high risk obstacles, we examine the lane and dynamic boundary as the region of interest to remove the background noises. It is emphasized that the ”noises” are not actually the false positives but the real objects that we do not consider as the dangerous ones. The false positives are excluded after several bad tracks. In this study the identification of high risk obstacles is not equal to the recognition of objects. It is known that radar is difficult to identify the objects so that the data fusion with images is highly desired. Although the scenarios in this paper are simple, the idea of dynamic boundary provides an insight to cope with the tracking discontinuity crossing different lanes. The abrupt variation of covariance error between lanes is a challenge for subsequent track to track sensor fusion.

In summary, this study examines a method to track the multiple objects and identify the high risk obstacles based on the radar sensor. The lost of target is compensated using the state prediction, and the false positives are excluded according to the number of bad tracks. Two boundaries are imposed as the region of interest on the multiple tracks. We experiment three scenarios and demonstrate the tracking performance on the vehicle and pedestrians. It is shown that the dynamic boundary is efficient to find out the high risk obstacles, and most of the background noises can be excluded. The lane boundary is effective to track the objects along the driving path, but the risk of transverse moving object might be underestimated.

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