Multiple Radar Sensor Fusion for Drone Surveillance in Urban Environment

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In recent years, the usages of drones are drastically increased. The ability of drones to take off in limited airspace, combined with their small size and high manoeuvrability means they can be launched and fly easily in the urban environment, and have potential to threaten critical infrastructures. The conventional radar, however, on the market today is less effective for such urbanized landscape because the radar line-of-sight is often blocked by the buildings. To monitor and track the drone in the urban environment and create continuous coverage, the distributed radar system consisting of a group of low-cost small radar sensors is thought to be a good solution.

This paper addresses the drone tracking by sensor fusion with such distributed radar system. As the drone is a kind of highly maneuvering target, the different target dynamic models and adaptive filter algorithms are developed, in order to figure out the model that can provide good performance to describe the motion of drone target. In terms of multiple radar sensor fusion, both data-level sensor fusion and track-level sensor fusion are studied. In addition to the theoretical and simulation analysis, a concept demonstrator is built by using three units of low-cost short-range radars to form a small radar network. The field trials and experimental results validate the feasibility of drone tracking by multi-radar sensor fusion.

I. Algorithm Development

A. Target Dynamic Model and State Prediction

As the drone often behaves very differently along its trajectory, the target dynamic model must be able to handle the highly maneuvering motion. The Constant Velocity (CV) model, Constant Acceleration (CA) model, Singer model, Constant Stop (CS) model (this model is designed for drone hovering in horizontal plane), Constant Turn (CT) model, and Frenet-Serret (FS) model are studied [1-2], together with the Kalman filter, extended Kalman filter and invariant extended Kalman filter. Then, a framework of simultaneous multiple dynamic models (IMM) is developed, which uses multiple target dynamic models at the same time (with probability and weight added) to describe the drone's true motion as much as possible so as to alleviate the effect of kinematics uncertainties on its tracking performance.

Figure 1 shows the tracking results of two real drones. We have their GPS data and then we inject the position errors with standard deviation of 3 m in x, y, z to the GPS data to simulate the measurements, and then track the drone. The figure shows the tracked position, ground speed and heading of the two drones by using IMM dynamic model (CV + CA+ CT + CS).

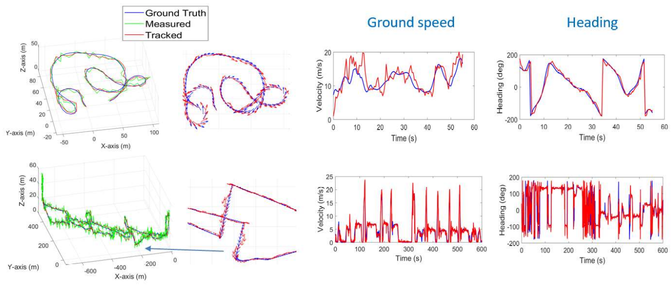

Figure 1: tracking results of two real drone trajectories

B. Data-level sensor fusion and track-level sensor fusion

Two levels of sensor fusion are investigated. One is data-level sensor fusion and the other is the track-level sensor fusion. The data-level sensor fusion is performed within a small cluster of sensors, where the measurement data of the sensors are directly put together to do the measurement-to-track association, while the track-level sensor fusion is done among different clusters of sensors to perform the track-to-track association.

For measurement-to-track association, it is required to solve the ambiguity problem: a measurement may be located in the gate of more than one track and a track may have more than one measurement in its gate. The Multiple Hypothesis Tracking (MHT) algorithm [3] is developed and applied to measurement-to-track association. The key strategy is: the difficult data association decisions are deferred by keeping multiple hypothesis track active until more data are receive, and at each time step, output the most likely hypothesis tracks. If the clutters or false alarms are too dense, the Probability Hypothesis Density (PHD) filter [4] could be applied before the MHT tracker to suppress the false alarm first. For track-to-track association, the covariance intersection algorithm [5] is employed to fuse the state estimation and state covariance of two associated tracks and yield the global system track.

Figure 2 shows the MHT tracking results of 3 simulated drones. We suppose false alarms occur at each time step in the area of 400 m by 700 m and the missed detection also exists with detection probability of 0.97. It is seen the tracking result is good.

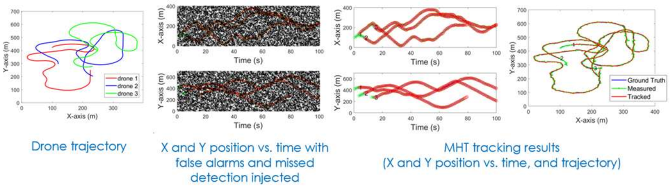

Figure 2: MHT tracking results of three simulated drones

II. CONCEPT DEMONSTRATOR AND EXPEIRMENTAL RESULTS

To validate the developed algorithm and the feasibility of drone tracking by sensor fusion, we use 3 units of extremely low-cost K-band FMCW radar to form a small radar network, as shown in Figure 3. The detection range of this radar is very short and the antenna sidelobe is a bit high but it is enough to validate the developed algorithms. 3 radars are deployed as co-located with each radar looking into the different directions, and totally provide the azimuth coverage of about 50 degrees. The data update rate of each radar is about 166 ms.

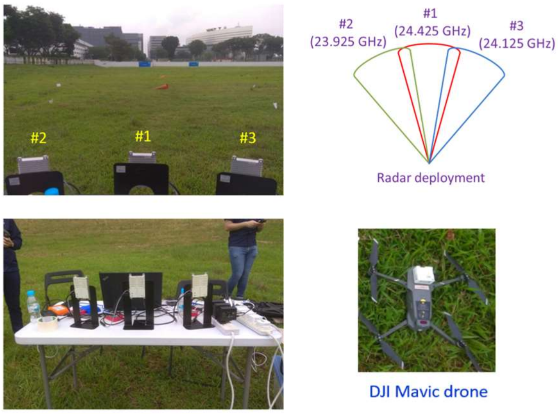

Figure 3: Small radar network and drone trial

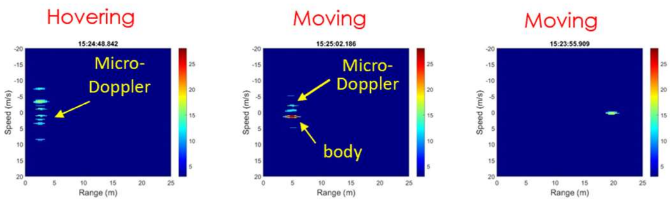

Figure 4: Range-Doppler map with drone detected

Figure 4 shows the measured range-Doppler map for the DJI Mavic drone. Then CFAR detection and drone classification are performed. The features that could be used for drone classification include but not limited to: micro-Doppler features, RCS, moving speed of main body, distance between two frequency peaks and heading changing rate etc. After that we do data-level sensor fusion and drone tracking, and compare the tracking results with the drone GPS trajectory. The drone GPS data is recorded with the position accuracy of about 2 m and time accuracy of 0.1 second.

Figure 5 shows the sensor fusion and drone tracking results for a triangle trajectory. It is observed that each radar can only detect a segment of the drone trajectory. After the data fusion of three radar sensors, the entire drone trajectory can be detected and tracked with the MHT tracker. Similar to Figure 5, Figure 6 shows the measurement results of sensor fusion and drone tracking where the drone has figure of 8 trajectory.

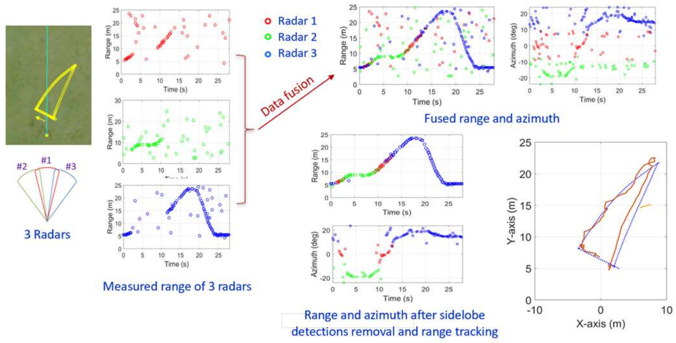

Figure 5: Sensor fusion and drone tracking results with triangle trajectory

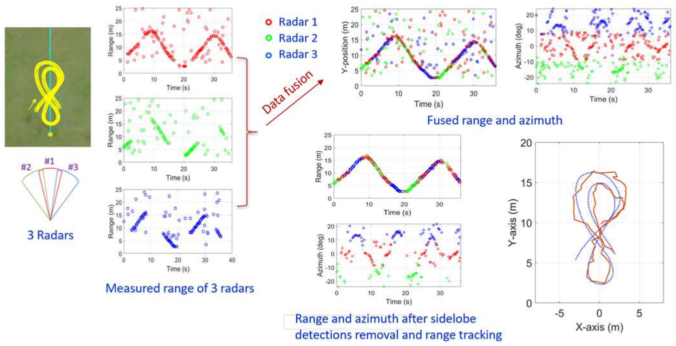

Figure 6: Sensor fusion and drone tracking results with figure of 8 trajectory

A few field trials are conducted with this concept demonstrator. The experimental results validate the feasibility of the drone tracking by multiple-radar sensor fusion and performance of our developed algorithms. The next step is to work with more operational radar (detection range up to 1 km) and conduct more trials in different urban environment to further optimize the system and algorithms.

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