Passive Sensor Processing and Data Fusion for Drone Detection

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ABSTRACT

Detecting micro drones is a difficult task, given the small sensor signature and high possible speeds they can achieve. Due to the variety of drone models and environmental conditions, one sensor type alone cannot detect all drone types with high reliability. Therefore, we propose a set of heterogeneous sensors combined with a sensor data fusion method to use their strengths and diminish the weaknesses. We describe below an RF sensor to capture the uplink and downlink of the Unmanned Aerial Vehicle (UAV), an acoustic sensor for the rotor noise, a passive radar system using the mobile network and multi hypotheses tracking for the fusion of sensor data.

1.0 INTRODUCTION

Passive sensor array system plays a crucial role in identifying the target of interest without emitting a signal. RF-emitter localization techniques are often based on the received signal strength (RSS), measured time of flight (ToF), measured time difference of arrival (TDoA), and measured direction of arrival (DoA) of signal to localize the RF-emitter [4]. In this paper, we propose the passive array system with a switched receiver system and its application in estimating UAV controller signal and UAV datalink.

In recent years, the interest in acoustic drone detection and direction finding has increased significantly, mainly due to its high precision and cost efficiency [13], [14]. During flight, UAVs emit sound waves whose characteristics depend on their design, environmental conditions such as air pressure, temperature and wind, and flight configurations such as speed and flight manoeuvres. The use of microphones arranged in groups exploiting the advantages of array processing methods such as beamforming allows determining the DoA of incident sound waves.

Passive radars, also commonly called PCL (Passive Coherent Location) systems, are in principle bistatic or multistatic radar systems exploiting illuminators of opportunity in its surrounding. A broad variety of frequency bands and transmission standards are applied as illuminators of opportunity in different passive radar systems using terrestrial digital TV (DVB-T), digital radio (DAB), analogue radio (FM), as well as mobile communication base stations. In the past years the department of Sensor Data and Information Fusion of Fraunhofer FKIE has conducted a wide range of experiments exploiting GSM (Global System for Mobile communications) and more recently also LTE (Long Term Evolution) base stations for the surveillance of small agile vessels in coastal regions or low flying aircrafts.

2.0 RADIO SIGNAL DIRECTION FINDING

DoA estimation is one of the most significant tasks of array antennas and there are multiple signal processing techniques available to perform the direction finding (DF) [1]. A group of antennas, called an array, is positioned in a particular order in space to estimate the direction of arrival of the incoming signal(s) [2]. The spatial-temporal estimation and filtering capability can be exploited for multiplexing co-channel users and rejecting harmful co-channel interference that may occur because of jamming or multipath effects [3].

2.1 Control Link & Data Link Signals

Control link and datalink are the two types of signals involved in the deployment of drones. Control link signals are at lower frequency range in order to attain a long-range controllability of a drone, whereas datalink are at high frequency range in order to obtain wider bandwidth to transmit data. Estimating the DoA) of the datalink and control link is the fundamental requirement of a radio frequency (RF) direction finder (DF) in UAV application. Mostly UAV control link signals are frequency hopping signals, where the carrier frequency is changing constantly within the assigned bandwidth (Fig. 1). Using frequency hopping signals, information can be protected from various kinds of noise and multi-path distortion and signal concealment and encryption are possible [5].

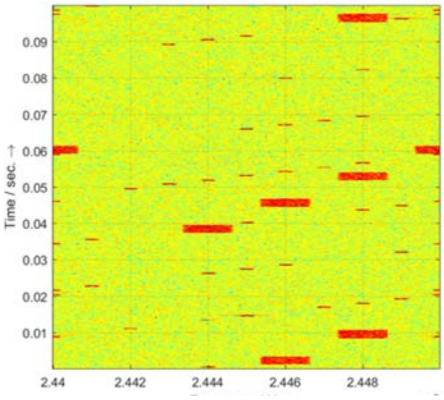

Figure 1 - Spectrogram of radio signals of UAV application

2.2 Trademark of Radio Signal Direction Finder

A radio signal DF can be used in cooperation with acoustic system, camera system and passive radar system to localize a drone. In absence of other systems, multiple RF DF systems are required to localize the target through cross bearing. A RF DF possesses an ability to estimate the DoA of both data link and control links signals, thereby it can help in localizing not only the drone (the usual target of interest) but also the drone's operating pilot. This feature acts as a trademark of a RF DF system in comparison to other systems used for monitoring. The range problem associated with the vision and acoustic-based techniques can be resolved by using high-gain receiver antennas together with a highly sensitive receiver system to measure the UAV controller signals. The issue of environmental noise can be suppressed by employing filtering techniques. Thus making a passive radio signal DF system a promising solution for long range detection and estimation of DoA [6].

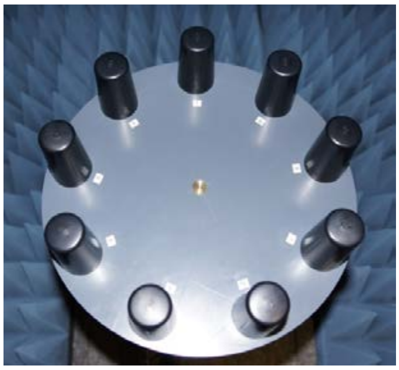

Figure 2 - Uniform circular antenna array

2.3 Significance of Array Geometry

The capability of an antenna array to estimate the DoA of a signal source in a three dimensional plane depends on its array geometry. The simplest form of array is a 1-D array, which is called as a linear array, could estimate the DoA of a signal only in azimuth. Whereas a two dimensional array, which is called as a planar array, is capable of estimating the DoA in both azimuth and elevation. Since drones possess a freedom of motion in all three axes, a 2-D array is required to estimate the DoA of the signals in both azimuth and elevation. Fig. 2 shows a uniform circular array (UCA) with nine vertically polarized isotropic antenna elements.

2.4 Switched Receiver System

Conventional data acquisition setup of an array requires the same number of receiving channels as that of the number of elements. This arrangement is often called as a full-channel receiver system but it leads to an enormous increase of cost, measurement complexity and overall size of the system. In order to mitigate the above-mentioned issues, an innovative data acquisition system with a reduced number of receiving channels has been developed. This type of architecture is called as a switched receiver system (Fig. 3). The UCA has been developed with two channels receiver system. Antenna 1 has a dedicated receiving channel whereas the other eight elements (Antenna 2 to Antenna 9) are connected to the other receiving channel through a switch. The acquired data from the two channels are pre-processed to construct a complete measurement matrix, which in turn is processed to estimate the DoA of the acquired signal [7]. An antenna array with a modular switched receiver system can be used to select the various element combinations. Thereby we build a complete measurement dataset with lesser number of receivers than the number of antenna elements, which is equivalent to a full-channel receiver system [8].

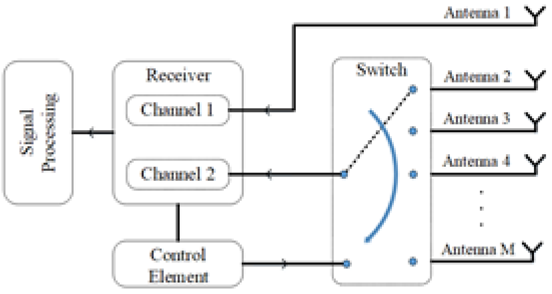

Figure 3 – Array antenna with switched receiver system

2.5 Direction Finding Techniques

Precise DoA estimation of a signal, accurate spatial distinguishing of the signal sources inside the array's field-of-view and high angular/spatial resolution of the system are some of the basic requirements of a direction finding algorithm. There are numerous direction finding techniques developed in the last decades to accomplish the above mentioned necessities. The direction finding algorithms can be broadly classified into the following three categories; namely, spectral-based, subspace-based and parametric algorithms [1]. Depends on the number of sources, computational effort, number and accuracy of the estimated parameters, angular resolution and SNR of the signals, a particular direction finding algorithm could be applied. Nowadays there are numerous artificial intelligence (AI) concepts are applied & tested in DoA estimation [6, 9, 10].

2.6 Significance of Calibration

Although there are various high quality DF processes available, these processes are sensitive to the errors involved in the complete system. These errors affect the amplitude and phase of the signal received by an array which results in poor DoA estimation. Basically the errors in an array antenna and in a receiver system, can be broadly classified into static and dynamic [11]. The electrical and mechanical manufacturing tolerances induce the static error, whereas the dynamic errors are highly dependent on temperature and operating conditions. Mutual coupling is another major cause of error, which leads to mismatches of phase and amplitude between the elements of an array. Due to non-ideal behaviour of the system the acquired signal deviates from the ideal behaviour. Calibration alleviates this non-ideal performance of the complete system (Fig. 4). Calibration can be classified into off-line and online. Off-line methods require sources with known direction of the incident signals, whereas online methods do not require a source with known signal direction. Off-line calibration method provides an increased accuracy in DoA estimation because of the reference measurements with known positions. More number of reference measurements yield a better result. This procedure does include an extensive lab facilities to perform numerous measurements, which implies increased cost and time. On the other hand, online calibration methods are time efficient and doesn't not include diverse reference measurements in the lab. Online calibration is performed on the field by utilizing the signal source(s). Thereby it takes the on-field scenarios (environmental noise, multipath scenarios and signal attenuation) into account. Since this method executes

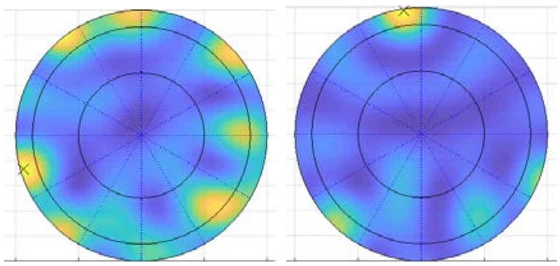

Figure 3 - DoA estimation: (a) uncalibrated (b) calibrated

the calibration and DoA estimation together, the accuracy of the estimation might be lesser than the accuracy of the estimation obtained through off-line calibration procedure. Calibration should be performed for both azimuth and elevation, so that a plausible and reliable results could be obtained in UAV application. In [12], a systematic study of various calibration processes has been performed on the UCA with measurement dataset. The radio signal direction finder is integrated with a navigation system to provide the actual position and angle of the system (Fig. 5). The earth fixed DoA estimate of the signals along with the sensor location are delivered to the fusion engine. The direction finder provides the flexibility to deliver the report to the fusion engine in the format it is required, so that the task of fusing this report with passive radar, acoustic system and imaging system is feasible.

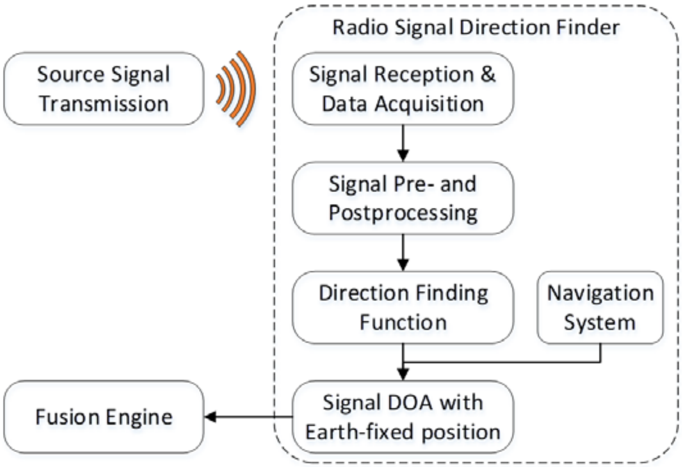

Figure 4 - Functional block diagram of a RF DF

2.7 Challenges in Urban environment

Multipath scenario, strong attenuation of signals and existence of diverse signals are the major points of consideration in an urban environment. Since the communication signals of most commercial and hobby grade UAVs are transmitted in the same frequency band as Wi-Fi and Bluetooth, it becomes challenging to detect and identify RF signals from the UAV controllers in the presence of these interferers [6]. In addition to the above mentioned challenges, multiple drone scenario will make the situation more demanding.

3.0 ACOUSTIC UAV DETECTION AND BEARING ESTIMATION

Acoustic sensors offer advantages in terms of detection range, which means that the sound signals can be detected from any angle, and line of sight is not mandatory. Innovative array processing methods allow the simultaneous detection and bearing estimation of several sound sources of same or different types. Challenges are posed partly by the low amplitudes of drone sounds in comparison to the ambient noise. To overcome this limitation, the characteristic frequency range of the drone and the continuity of the signal can be exploited. Nevertheless, the detection ranges are limited and depend strongly on the components used and the type of drone to be detected.

3.1 Acoustic Signal Characteristics

Extensive understanding of the UAV's sound signatures characteristics is required to adequately evaluate acoustic detection of drones [15]. To do so, the classical short-time Fourier Transform can initially be used to analyse the sound signals emitted by UAVs and to better understand how their properties could be extracted. Fig. 6 shows an example of the radiation spectrum of the sound wave emitted by a UAV in flight. The characteristic acoustic signal emitted by UAVs is composed of the propeller noise, the engine noise and other random broadband noise. The number and speed of the propellers induce the harmonic frequencies.

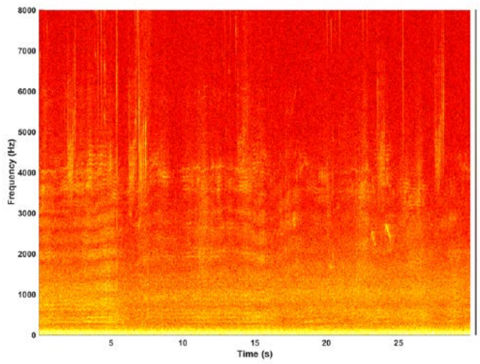

Figure 5 - Spectrogram of typical quadcopter data

3.2 Crow's Nest Array

To meet the requirements and challenges imposed by the acoustic detection and bearing estimation of drones, the compact experimental system shown in Fig. 7 was designed. This system is composed of a volumetric microphone array of 16 microphones randomly distributed within a sphere called 'Crow's Nest' Array [16]. Due to this specific volumetric arrangement, bearing angles can be determined with a full spherical azimuth and elevation coverage of 360° and 180° respectively. The microphone selection, their amplification and their sampling rate were selected considering the type of sound to be measured, as well as the bandwidth.

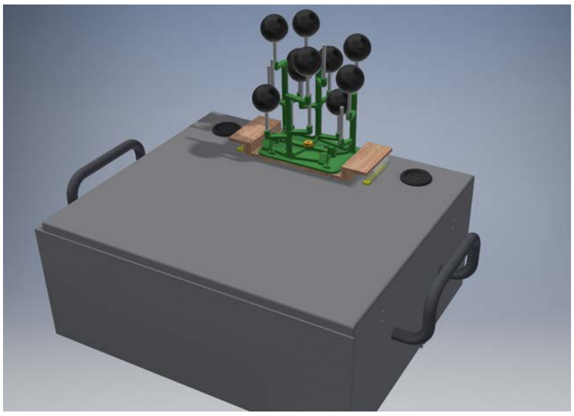

Figure 6 - Crow's Nest Array

3.3 Experimental System

The structure of the signal processing chain leading to source localization, in the project, is shown on Fig. 3.

3.3.1 Filtering

The first step of this schema after the digitalization of the recordings is to remove some of the noise. Therefore, the signals are initially band-pass filtered.

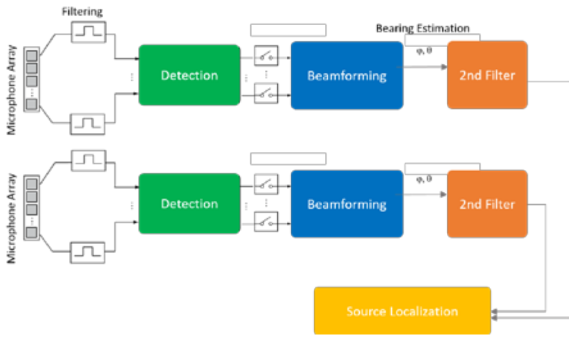

Figure 7 - Experimental System Flowchart

3.3.2 Detection

Subsequently, numerous signal processing methods have been implemented to efficiently detect drones. One of these methods selected the spectral lines separated by constant distances produced by drones on the spectrogram (see Fig. 6), in other words, the energy of harmonics, and then compared them with a threshold to produce a detection. This procedure proved to have a high positive predictive value, but also a high false discovery rate when sounds similar to drone sound where present, i.e. sounds of vehicles. Nowadays, drones can also be classified by AI methods. Indeed, very similar acoustic sounds, such as gunshots, can be distinguished from each other by using AI methods, such as Machine Learning (ML) and Deep Learning (DL) [17], therefore the distinction between different types of drones is also feasible. Feature extraction plays a crucial role especially in ML techniques. In fact, features are the signature of the specific event to be identified [18], and therefore must be specifically selected. It is also advantageous to have an adequate feature selection when using DL techniques, however the big data amount used plays a beneficial role in this case and can compensate for the preciseness of the features. Acoustic classification can thus substitute classical detection that used conventional signal processing methods [19].

3.3.3 Beamforming

The bearing estimation method used is the coherent broadband beamforming [16]. In this method, the acoustic wideband array signals are windowed, band-pass filtered and Fourier transformed. Subsequently, frequency-space vectors are generated, weighted according to the array geometry and summed up to produce a beam pattern. The estimated bearing angle of the UAV corresponds to the position of the main beam direction of the beam pattern [19]. This method has proven to be more accurate than other methods, such as the incoherent beamforming method.

3.3.4 Two-Step Filter

Achieving acoustic outdoor measurements also imply working with acoustical reflections and reverberations. Moreover, often the wanted signal is overlapping interference signals, which can lead to false bearing estimations. For example, wind and other ambient noise can affect the bearing of an approaching UAV, hindering the correct detection of sounds. That is the reason for the second filter present in the flow chart on Fig. 8. This filter uses the normalized power of the beamforming pattern, and is a 2-step filter (see Fig. 9). It combines a threshold filter and a median filter to ensure that the estimated bearing corresponds to a main beam direction of the beam pattern such as in Fig. 10, and not to the maximum value of a noise pattern (see Fig. 11). In other words, this second filter reduce false bearings.

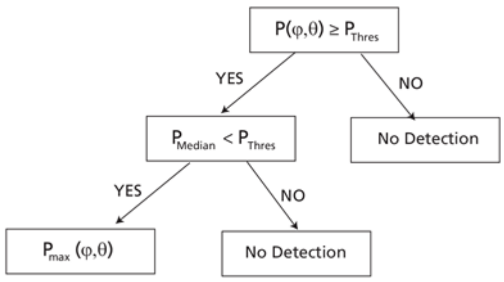

Figure 8 - Flowchart of the second detection method

3.3.5 Source Localization

The estimated DoA, azimuth and elevation angles can be independently sent to the fusion engine [21] in order to achieve source localization in cooperation with another sensor system, e.g. a second acoustic array, a RF DF system, or a passive radar system.

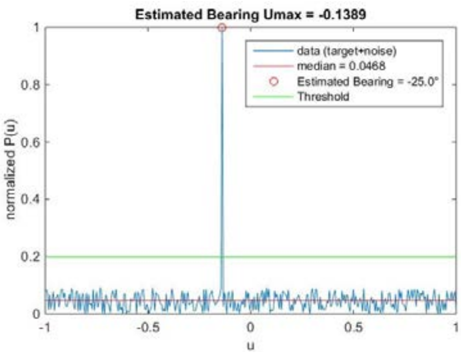

Figure 9 - Bearing estimation of an UAV

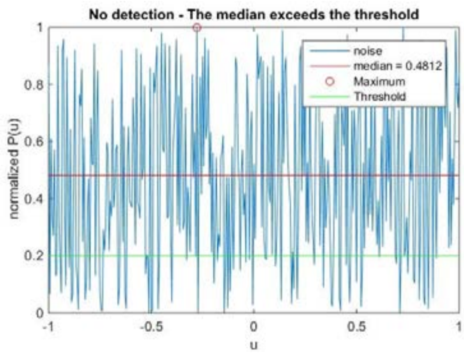

Figure 10 - Noise data and false bearing estimation

3.4 Experimental Results

In Fig. 12, one volumetric microphone array measured the emitted sound of one UAV in flight. To eliminate noise, such as wind or speech, from the measured sound signal, the data was processed using a band-pass filter with the lower cut-off frequency f_l=2 kHz and the upper cut-off frequency f_u=90 kHz. Since the UAV noise is a continuous signal, it was divided in the frequency domain into narrower windows of 400 samples and then averaged over one second to make it more robust against noise. Afterwards, one azimuth and elevation bearing angles were estimated for every second. The azimuth angles are shown along with their ground truth, which was provided by a navigation system on the UAV. Apart from a few outliers, the estimated bearing angles (orange dots) correspond very closely to the true values (blue dots).

4 PASSIVE RADAR

Another class of sensor systems that can greatly contribute to the multisensor task of UAV detection and tracking are passive radars. Passive radars, also commonly called PCL (Passive Coherent Location) systems are in principle bistatic or multistatic radar systems exploiting illuminators of opportunity in their surroundings. A broad variety of frequency bands and transmission standards are applied as illuminators of opportunity in different passive radar systems using terrestrial digital TV (DVB-T), digital radio (DAB), analog radio (FM), as well as mobile communication base stations. Fraunhofer FKIE currently focuses its passive radar research activities on the use of mobile communication base station illuminators GSM (Global System for Mobile communications) and LTE (Long Term Evolution), where a wide range of experiments have been conducted in recent years for the surveillance of small agile vessels in coastal regions or low flying aircrafts. See for example [22, 23]. In this chapter exemplary results of an experimental trial to detect and track a UAV in a GSM passive radar scenario are shown.

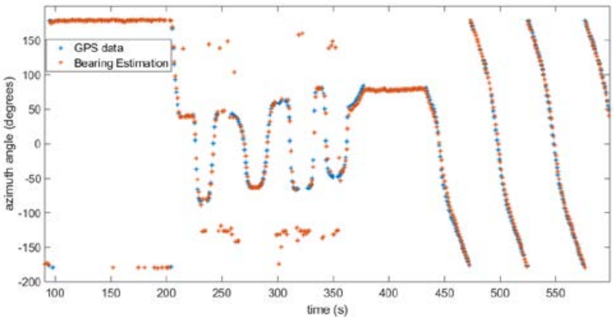

Figure 11 - DoA estimation results (orange dots) for azimuth angles compared with ground truth (blue dots)

4.1. Problem Formulation

One of the challenges when applying GSM in passive radar is the relatively low transmit power of its base stations resulting in a low signal-to-noise ratio (SNR) of possible target reflections. If additionally the target radar cross section (RCS) is low, which is the case for small commercially available UAVs treated in this work, successfully detecting and tracking such a target can become very difficult due to the basic principles of traditional tracking methods.

In classical radar processing the target tracking task is generally divided into a detection and a tracking stage. In the detection stage a threshold is applied to the raw radar signal processing results. The resulting detections correspond to either actual target reflections or false alarms due to noise and clutter. In the following tracking stage target tracks are formed, updated, or discarded based on the previously obtained detections. In circumstances where the target SNR is high this procedure generally performs well, as a threshold can be found that results in high probability of target detection while at the same time exhibiting a low false alarm rate. If a low SNR target, like for example a drone, is present, thresholding generally results in missed target detections or a high false alarm rate.

To bypass these limitations of traditional "Detect-before-Track" an alternative approach named Track-before-Detect (TbD) has been proposed. In Track-before-Detect methods, the tracker is fed with raw unthresholded signal processing results. Through statistical tracking methods, hypotheses of targets are established over time before a decision is made about their actual existence. This allows for an integration of weak target reflection over time and therefore potentially unmasks weak targets previously hidden in noise. A particle filter for Track-before-Detect in GSM passive radar, developed in [24] and extended to handle complex valued measurements and fluctuating targets in [25, 26] is applied to experimental data using a UAV as cooperative target.

4.2. Track-before-Detect Particle Filter

The passive radar system delivers a three-dimensional complex valued data cube at the output of its signal processing stage. Its dimensions are bistatic range, bistatic range rate, and azimuth, corresponding to time difference, Doppler shift and direction of arrival, respectively. The TbD method applied here aims to detect and track the reflection of a UAV in this measurement domain. This avoids nonlinearities introduced by the transformation to Cartesian space and constitutes a good compromise between centralized and distributed fusion as described in [27]. A target with Cartesian position $\mathbf{q_k}$ and velocity $\mathbf{v_k}$ at measurement $\mathbf{k}$ exhibits a bistatic range according to

$$r_k = ||\mathbf{q}_k - \mathbf{q}_{\text{tx}}|| + ||\mathbf{q}_k - \mathbf{q}_{\text{rx}}|| \tag{1}$$

where $\mathbf{q_{rx}}$ is the position of the passive radar and $\mathbf{q_{tx}}$ the position of the illuminating base station. Due to the Doppler effect the signal reflected by the target exhibits a range rate value of

$$\dot{r}_k = \left(\frac{\mathbf{q}_k - \mathbf{q}_{\text{tx}}}{||\mathbf{q}_k - \mathbf{q}_{\text{tx}}||} + \frac{\mathbf{q}_k - \mathbf{q}_{\text{rx}}}{||\mathbf{q}_k - \mathbf{q}_{\text{rx}}||} \right)^T \cdot \mathbf{v}_k \tag{2}$$

at the passive radar receiver. The target azimuth is given by the direction of arrival of the reflected signal according to

$$\varphi_k = \text{atan2}(x_k - x_{\text{rx}}, y_k - y_{\text{rx}}) \tag{3}$$

where atan2 is the four-quadrant inverse tangent and $\mathbf{x_k}$, $\mathbf{y_k}$, $\mathbf{x_{rx}}$, and $\mathbf{y_{rx}}$ are the Cartesian x- and y-coordinates of target and receiver, respectively. As described in [24] the values of equations (1) to (3) are part of the target state. The target state is assumed to evolve according to a linear nearly constant velocity model over measurement intervals $\mathbf{k}$, as given in [27]. The target reflection in the data cube is modelled as a Gaussian function spread over a finite number of neighboring measurement grid points, as previously mentioned in [28, 24]. The well known Sequential Importance Resampling (SIR) particle filter [29] is applied to track the target states of the particle set. In the algorithm a target is declared detected when the majority of all particles in the particle set declare a target present, based on an auxiliary target existence state variable [28]. The estimated target state is then given by the arithmetic mean of all particle states with existing target.

4.3. Experimental Trial

Figure 12 - Passive radar system components set up on the roof of a building

During the experiment of about 6 minutes duration, a DJI Matrice 210 V2 served as a cooperative target. It is a quadcopter with a size of 883 mm x 886 mm x 398 mm with extended propellers and legs. Its weight is about 4.8 kg. The drone was equipped with a GPS (Global Positioning System) logger to provide ground truth for evaluation. Similar to previous UAV passive radar experiments of Fraunhofer FKIE in [23], the passive radar system COMET was set up on the roof of a building on the site of the institute in Wachtberg, Germany, as can be seen in figure 13. COMET is a USRP (Universal Software Radio Peripheral) based system, which is in its current implementation capable of simultaneously receiving 6 GSM broadcast channels of 200 kHz channel width. The antenna of the systems consists of 16 columns of Vivaldi antennas in a linear array. In total 5 GSM basestations in the area of the trial were suited as illuminators and processed by the system. During the trial, the UAV was flying an x-shaped course in a distance between 60 m and 320 m from the position of the passive radar system and approximately in the same height. Figure 14 shows the flight course and the position of COMET in a Cartesian coordinate system, where the y-axis represents north and the x-axis east.

4.4. Evaluation

For the evaluation of the experiment a GSM base station, operating at a transmit frequency of 945.8 MHz, was chosen. It was situated in a distance of about 800 m north east of the receiver position. The acquired data was processed in the passive radar system with an integration time of 0.5 s. 40,000 particles were used in the evaluation run. Newly born particles were placed in the measurement space at positions were the absolute values of the measurements exceeded a CFAR (Constant False Alarm Rate) threshold as introduced in [29].

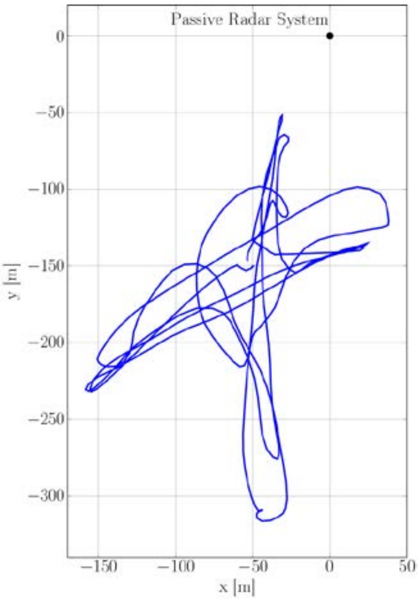

Figure 13 - Cartesian course of UAV flights logged during experimental trial

The diagrams in figures 15 to 17 show the expected bistatic range difference (bistatic range minus distance from BTS to receiver), bistatic range rate, and azimuth calculated from the GPS ground truth together with the respective estimated target state dimension of the Track-before-Detect particle filter if a target was declared detected.

The first 25 measurements are the lift off phase and between measurement 170 and 215 target was hovering in the air. During these time instances, the target should not be detectable by the method. Due to clutter sources in the area of the trial, which are interpreted as target originated reflections by the method due to the simple clutter model, the method detects false targets. Outside of these critical sequences, the target is detected almost continuously and with a remarkable high estimation accuracy in the bistatic range and bistatic range rate dimensions. The remaining inaccuracies in the azimuth domain can be attributed to clutter sources between azimuth values of 160° and 180° on the site of the trial. The offset in bistatic range between measurements 25 and 93 results from the wide target reflection peak in the range domain due to the low GSM signal bandwidth of 81.3 kHz.

Calculating the RMSE (Root Mean Squared Error) values for each observable dimension of the target state over the whole experiment results in 163.3 m for the bistatic range, 5.71 m/s for the bistatic range rate, and 17.95° for the azimuth. Note that these values are including the false detections of the lift off and hovering phase.

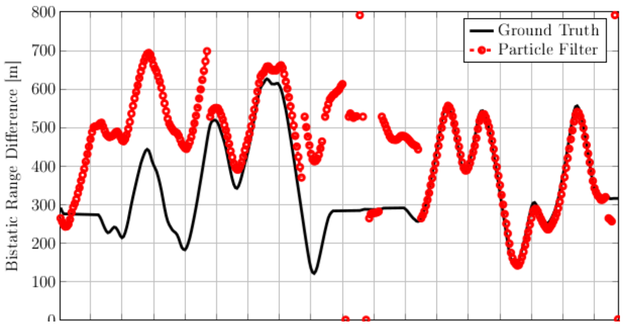

Figure 14 - Bistatic range difference of UAV from ground truth and corresponding state component of TbD particle filter

During a 50 s period, between measurements 230 and 280, the method performs particularly well. Here RMSE values of 16.3 m in bistatic range, 1.33 m/s in bistatic range rate, and 4.83° in azimuth are achieved. These values can be interpreted as optimistic expectations if the detection of false targets due to clutter can be avoided. It should be noted here that the influence of the false target, while the actual target is located in the blind zone of the system, may be significantly reduced by fusion of multiple bistatic pairs or multiple other sensor systems as previously mentioned. Fusion of multiple bistatic pairs is crucial for accurate Cartesian localization results in passive radar using mobile communication signals.

Detecting and tracking UAVs is a challenging task for passive radar systems using mobile communication base stations as illuminators of opportunity. Track-before-Detect methods have previously shown to be

suitable for detecting weak targets in simulations. In this chapter an experiment conducted with a small quadcopter is presented and evaluated. The Track-before-Detect particle filter achieves a high detection rate of the target while also achieving a remarkable estimation accuracy in the system measurement space. These results show that passive radar, as applied here, can contribute greatly to the task of detecting and tracking UAVs in a future fusion of heterogeneous sensor systems.

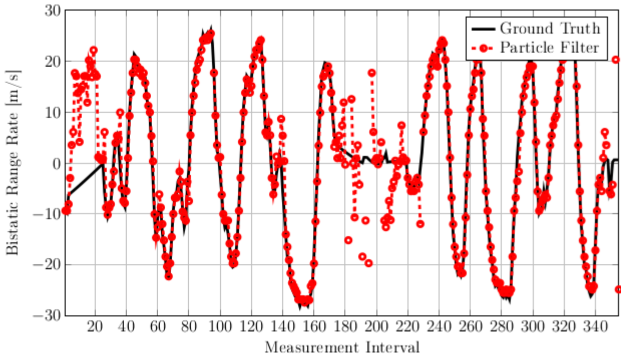

Figure 15 Bistatic range rate of UAV from ground truth and corresponding state component of TbD particle filter.

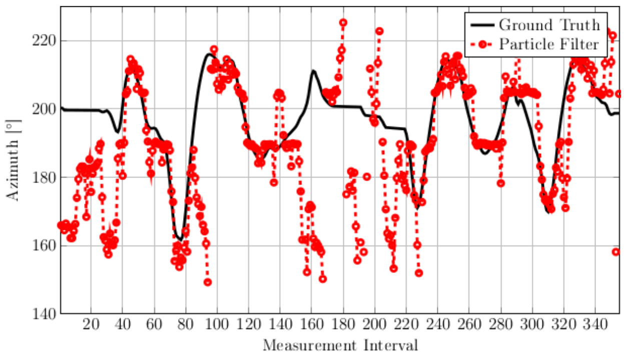

Figure 166 - Azimuth of UAV from ground truth and corresponding state component of TbD particle filter.

5.0 FUSION ENGINE

The fusion engine fuses the UAV observations from the various sensors and provides the results to the command and control center in realtime to enable instant response capabilities. Each sensor component provides processed observations in the form of a target information vector to the fusion center. The target information vector includes all possible parameters the sensor is capable of estimating. For example, in the case of passive radar this vector may contain target range from sensor, bearing and target doppler information. The interface between sensors and fusion can be modified to fit specific sensor parameters.

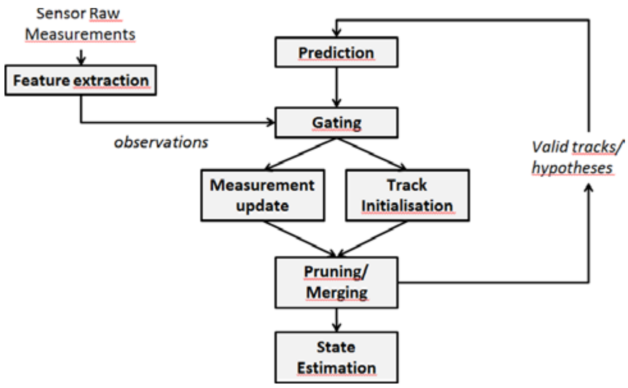

Figure 18 - Multi Hypotheses Tracking block diagram

An appropriate fusion strategy can be chosen based on the available type of sensors for the system and the type and quality of data they provide to the fusion center. Based on the type of data a sensor can provide, there are three types of sensors:

- Bearing sensors - a single sensor provides only bearing information
- Sensors with localization capability - a single sensor provides enough data to localize targets
- Tracking sensors - these sensors provide tracks of detected targets and maintain a unique identification over time

Within this work a centralised data fusion system based on a multiple hypothesis tracker (MHT) [30][32] is implemented. For the generalisation of the implemented solution to more or different types of sensors, a model association method is developed where specific sensor models are assigned automatically based on the sensor input data. This is possible by defining the specific type of expected observation parameters from each sensor. Together with the adaptive interface this level of abstraction allows the fast integration of other sensors.

Fig. 18 depicts a block diagram of an MHT procedure. At each time step target states are propagated using dynamic models for possible target behaviour. When target observations are provided by the sensor, hypothesis are formed covering the various possible cases i.e. which target does this observation belong to, or is this target a false alarm? The target state and covariance update for each hypothesis is done using extended Kalman filter update equations. For hypothesis reduction, gating as well as hypothesis pruning and merging is used.

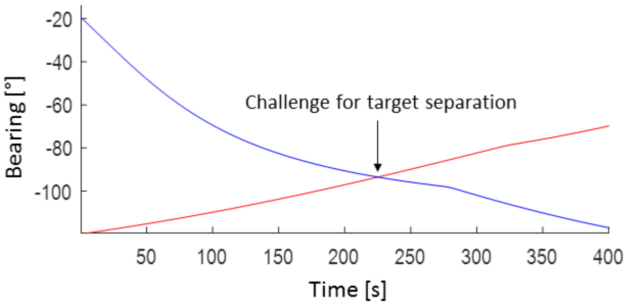

Figure 19 - Bearings of the two targets as seen by the camera

For method verification camera and radar sensor are simulated detecting two targets. Both targets are geographically separated, however they have the similar/close bearings approximately in the middle of their trajectory seen in Fig. 19. Thus a bearing only sensor such as the camera sensor can not separate the two targets. For data generation, 1° bearing estimation error is used for the camera sensor and 4° bearing estimation error and 10m range estimation error is used for the radar sensor. The tracking results for the scenario when only the radar sensor (dashed lines) and both radar and camera sensors (continuous lines) are used are shown in Fig. 20. By using both sensors an improvement in the location estimation when using both sensors can be noticed. Since an additional sensor is used, measurement to track association errors are likely, which can be seen by increase in the position error when the targets have similar bearings.

We also conducted tests with real sensors within a civilian research project [31]. Due to time constraints we were not able to fully evaluate our approach, but we were able to demonstrate our system in field experiments.

Within the project had we had four different sensor types with different measurement units:

- Radar: Azimuth, Range
- RF: Azimuth
- Acoustic: Azimuth, Elevation
- EO/IR: Azimuth, Elevation

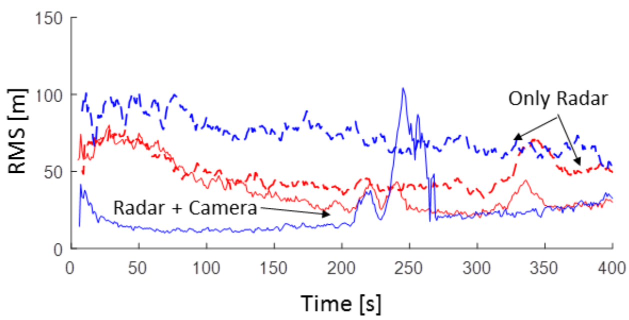

Figure 20 - Root mean square error for each of the targets

During the tests up to 11 sensors were present, one radar and RF sensor, five Acoustic sensors and four EO/IR sensors. The fusion engine had to process up to 100 measurements per second with largely varying intervals and delays. While one camera and the RF sensor could deliver up to 30 measurements per seconds alone, the spinning radar had an update rate of roughly 2.5 seconds. The acoustic sensor delivered measurements up to 10 Hz, but had a delay of about second due to processing. We have had different sensor setups, geometries and flight patterns and have gained experience with the system:

- Track initialization with radar is possible over great distances, however the tracks show a high localization error and large update interval (see Figure 21 (a))

- The tracks can be refined with measurements from other sensors to minimize localization errors (see Figure 21 (b, c))

- As the tracks are supported by measurements from sensors with a high confidence, the fusion engine will continue the tracks, even if the target moves into sensor shadows (see Figure 21 (d)). This enables the uses of sensor nets in complex environments, e.g. urban scenarios.

6.0 CONCLUSION

Detection and tracking of drones are challenging tasks, but these can be carried out even with the restriction to passive sensors only. We have shown that the detection can be achieved with acoustic, RF and PCL sensors. Depending on the scenario and the environment, the use of multiple sensors may be necessary. We used a multi hypothesis tracker to perform the tracking of drones in a multi sensor setup. The use of these methods enable the use of multiple heterogeneous sensors in a single system.

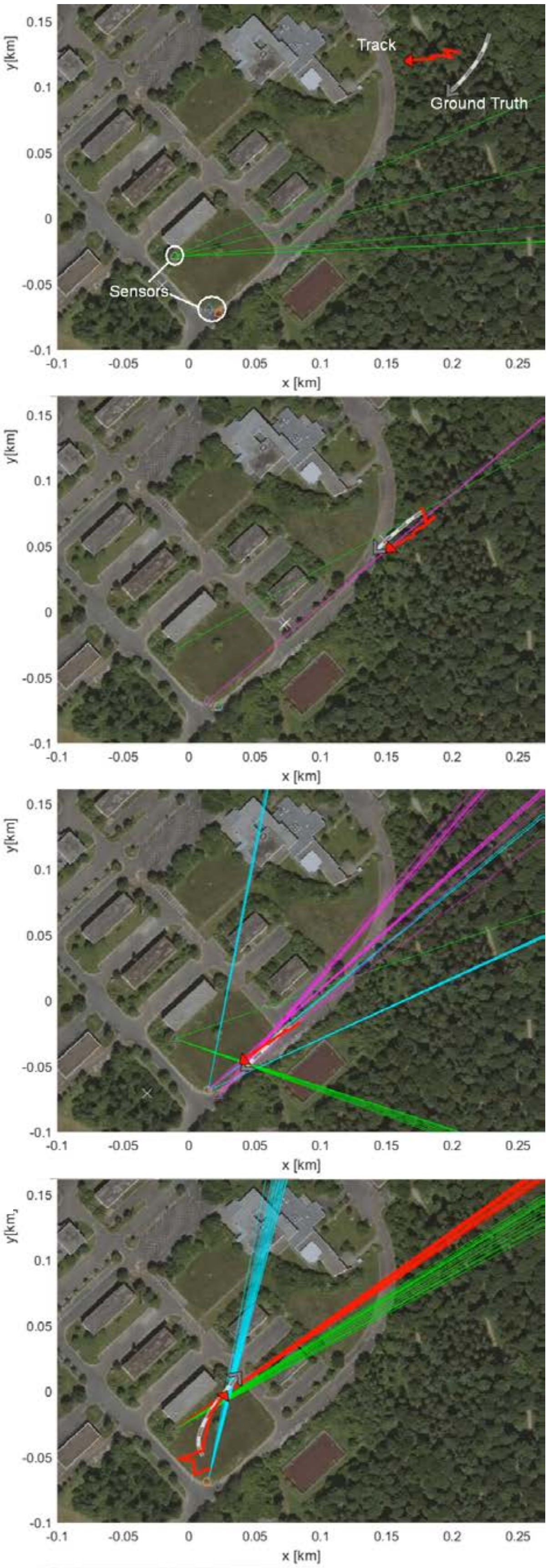

Figure 221 - Fusion Engine results: Track initialization with radar (a), Track refinement with RF (b), Track refinement with EO/IR sensors (c), Track continuation after flying through the sensor shadow (d)

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