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3D Detection of Flying Insects from a Millimeter-Wave Radar Imaging System

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Abstract – Studying the movement patterns of small flying insects, such as pollinators, is a major challenge in biology. Here we introduce an original approach to track the 3D motion of flying insects using a millimeter-wave radar imaging system. 3D images are obtained from the beam scanning of a Frequency-Modulated Continuous-Wave and Single-Input Multiple-Output radar operating at 77 GHz. We derive the flight trajectory of insects and mitigate the electromagnetic clutter from the 3D radar images. To illustrate our approach, 3D flights of isolated bumblebees are radar tracked in a limited volume during 5.2 minutes with a time resolution of 60ms. The radar tracks are compared with video recordings for validation purpose. The tracking volume of an insect using a single radar is estimated at 5.3m³, and we show that the volume can be tripled when three radar imaging systems are deployed. Finally, we discuss how our new radar-based technique can be extended to track a broad diversity of small flying animals at different spatial scales and simultaneously in the lab and in the field.

Keywords – *Animal tracking, Millimeter-wave, Radar imaging*

22 **1 Introduction**

23 How flying insects, such as bees, wasps, flies and butterflies, move across landscapes to exploit plant
24 or host resources is a central question in biology, with far reaching applications for pollination, food
25 production, pest management and conservation. However, direct observations of the foraging patterns
26 of these small insects in naturalistic conditions have always been difficult (Freeman, 1968). For instance,
27 tracking a flying bee requires to monitor a small target (typically less than 2cm long) with high velocity
28 (up to 20km/h), moving in the 3D space, and sometimes over several square kilometers over many days
29 (Chittka, 2022). This is out of reach with current tracking technologies despite recent technical advances
30 (Kays et al., 2015).

31 In the last decades, many remote sensing technologies (optical, radio but also by other means) have
32 been explored to study insect behaviour (Drake and Reynolds, 2013; Kissling et al., 2014; Reynolds
33 and Riley, 2002). Emerging technologies for entomology have been reviewed recently in (Rhodes et al.,
34 2022; van Klink et al., 2022). Many of these technologies aim at recording the movement patterns of
35 pollinators while foraging on flowers. High Frequency (HF) Radio Frequency IDentification (RFID)
36 sensors (Kim et al., 2019; Ohashi et al., 2010), computer vision (Crall et al., 2018; Manoukis and Collier,
37 2019), and motion detection cameras (Crall et al., 2015; Lihoreau et al., 2016a) have been used to
38 record nest entrance and flower visits by individual bees. These techniques can be applied to monitor
39 the foraging activity of bees and estimate their flower visitation sequences over long periods of time (up
40 to weeks). However they provide no information about the flight trajectories and search patterns of bees
41 between flower visits. At small spatial scales, flight paths can be recorded with optical approaches. For
42 instance a single Infra-Red (IR) camera has been used to track bumblebees and moths equipped with
43 photoluminescent tags outdoor within about 2.0m² (Walter et al., 2021). A so-called Fast-Lock-On (FLO)
44 tracking system based on a single stereo camera and an IR illumination source (Vo-Doan et al., 2023)
45 enabled for high-resolution video recording of a lightly-tagged flying insect motion during natural
46 behavior. High-speed cameras have also been used to study the 3D movements of untagged bees in

47 the lab (Ings and Chittka, 2008; Lihoreau et al., 2016b) and outdoor within about 27m³ (Sun and
48 Gaydecki, 2021), but these approaches are highly sensitive to illumination and typically require several
49 cameras to resolve 3D tracks.

50 The aforementioned techniques enable observations of complete behavioural sequences in small
51 laboratory setups where naturalistic behaviour may be expressed only to a limited extent, or partial flight
52 paths in the field. Radio-Frequency (RF) technologies, such as harmonic radar (Riley et al., 1996;
53 Woodgate et al., 2017), radio-telemetry (Kennedy et al., 2018), Vertical-Looking Radar (VLR) (Drake
54 and Reynolds, 2013) provide means to study the spatial movements of flying insect over larger spatial
55 scales in the field. An extensive review of these RF-based entomology techniques can be found in
56 (Drake and Reynolds, 2013; Kissling et al., 2014). Scanning harmonic radar and radio-telemetry enable
57 to detect insects in 2D (range-azimuth) at up to several hundred meters but at the cost of poor spatial
58 resolution (down to ten meters), poor temporal resolution (down to a second), and large power
59 consumption (up to tens of kW) (Kissling et al., 2014; Psychoudakis et al., 2008). These long-range
60 tracking approaches also require to equip the insects with large tags whose mass and size may impact
61 the insect's flight: typically about 12 mg and 16 mm long in the case of harmonic radar (Drake and
62 Reynolds, 2013; Kissling et al., 2014; Psychoudakis et al., 2008); typically 300 mg and a footprint of
63 100mm³ for radio-telemetry (Kim et al., 2019). Harmonic radar allows only detection of one transponder
64 at a time, whereas radio-telemetry allows detection of multiple tags simultaneously. However, harmonic
65 transponders are very light-weight compared to the active tags used in radio-telemetry and thus allows
66 them to be used on a wider range of insects. The effect of the tag weight on the insect behaviour has
67 been studied for terrestrial and flying insects in e.g. (Batsleer et al., 2020; Kaláb et al., 2021) and recently
68 reviewed for the case of beetles in (Růžičková and Elek, 2023). These techniques, initially implemented
69 with a stationary transmitter, have recently been integrated on Unmanned Aerial Vehicles (UAVs) (Ju
70 and Son, 2022; Kim et al., 2022; Lavrenko et al., 2021; Tahir and Brooker, 2015) to improve the tracking
71 distance and reduce power consumption. Similarly, the optical sensor used in (Walter et al., 2021) was

72 estimated to be sufficiently light-weight to be mounted on a UAV, thus opening the possibility to track
73 flying insects over larger spatial volumes. Moreover, the so-called FLO tracking system developed in
74 (Vo-Doan et al., 2023) has been integrated on a UAV to track a tagged insect. Recently, a high-
75 resolution camera mounted on a static UAV hovering over a field allowed to track butterflies in an area
76 of about 2,000 m² (Margerie and Monmasson, 2024). Although promising results were obtained, tracking
77 flying insects using UAV-integrated tracking radio-systems has not been demonstrated yet.

78 Here we introduce a millimeter-wave radar imaging system to track the 3D motion of flying insects with
79 a high spatio-temporal resolution, and at various spatial scales. In contrast with optical-based
80 techniques that require multiple cameras to resolve the insect position in 3D (Lihoreau et al., 2016b), a
81 single radar sensor can be used. Radars are not affected by the brightness and thus outside
82 observations are possible irrespective of light conditions (even at night-time). Radars can be tuned in
83 order to control resolution and detection range to the targets. Finally, millimeter waves can penetrate
84 the opaque thin nets or thin plexiglas walls, enabling to track insects in cluttered environments. In a
85 preliminary study (Dore et al., 2020), we demonstrated that bumblebees can be detected up to 2.0
86 meters (± 0.05 meters) using such a mm-wave radar. The detection range increases with the transmitted
87 power and the size of the target (in most cases) and thus the use of a low-power mm-wave radar sensor
88 and the small size of the target only enable detection at small distances. The detection range for such
89 small targets is very small compared to that obtained from other aforementioned techniques such as
90 harmonic radar and RF telemetry. However a recent study (Dore et al., 2020) showed that a mm-wave
91 radar allowed to track in 3D with high-resolution which is interesting from an ethological point-of-view
92 even at small spatial scales (Ings and Chittka, 2008; Lihoreau et al., 2016b). In this previous study (Dore
93 et al., 2020), the basic algorithm used to mitigate the electromagnetic clutter drastically limited the
94 number and duration (<2 seconds) of motion tracking. In this new study, we establish, for the first time,
95 the proof-of-concept of a new detection algorithm to detect a flying insect over longer periods (several
96 minutes) using a home-made millimeter-wave imaging system. To do so we tagged bumblebees with a

97 small hollow aluminum cylinder (1.5 cm long, 1.0 mm in diameter and 100 μm of thickness and 50 mg
98 of mass) and released them alone in a flight chamber for 37 minutes. We then applied an original
99 detection algorithm based on the mitigation of the electromagnetic clutter from isolines in the 3D radar
100 images. Using a categorical classification technique, we compared the 3D tracks of flying bumblebees
101 derived from the radar system with those obtained by using video recordings.

102 **2 Materials and methods**

103 **2.1 Millimeter-wave radar imaging system**

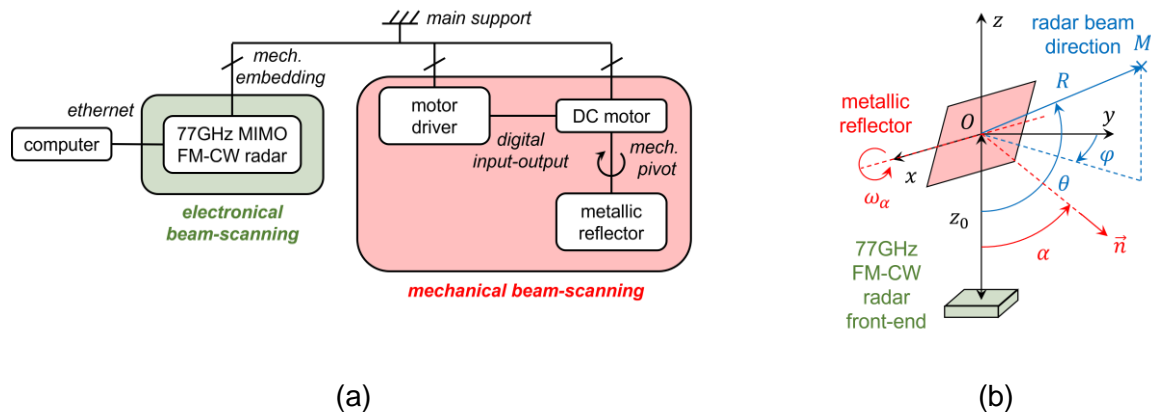
104 **2.1.1 Definition of the transmitted and received radar signals**

105 The block diagram of the radar imaging system is shown in Figure 1a. The system includes a Frequency-
106 Modulated (FM) Continuous-Wave (CW) Single-Input Multiple-Output (SIMO) radar commercialized by
107 INRAS GmbH (INRAS, 2023). The radar transmits periodically the waveform displayed in Figure 2.
108 During each period or repetition time t_{rep} , the frequency-modulated signal, i.e. the sweep, with ramp
109 duration t_{ramp} ($=205\mu\text{s}$), carrier frequency f_c ($=77\text{GHz}$) and modulation bandwidth B ($=3\text{GHz}$) is
110 transmitted by N_{Tx} ($=1$) transmitting antenna. The electromagnetic power P_{Tx} radiated by the radar is of
111 10dBm. The transmitted signal is then backscattered by the scene, received by N_{Rx} ($=16$) antennas of
112 the radar and processed by a Field-Programmable Gate Array (FPGA) that is connected to a computer
113 via an Ethernet link. Transmitting (T_X) and receiving (R_X) antennas are identical vertically-polarized
114 rectangular patch antenna arrays, printed on the same circuit board. At every moment nt_{rep} , where
115 $n=0, 1, \dots, N_L-1$, the sweep is generated by the transceiver of the radar front-end and radiated by the
116 T_X -antenna. The N_L time samples $0, t_{\text{rep}}, 2t_{\text{rep}}, 3t_{\text{rep}}, \dots, (N_L-1)t_{\text{rep}}$ are usually called the slow time
117 samples. Let N_S be the number of so-called fast time samples used to digitize the waveform of Figure
118 2. The maximum detection range, denoted R_{max} , of the sensor is given by $\frac{N_S \Delta R}{2}$, where N_S denotes the
119 number of fast time samples and ΔR is the theoretical range resolution of the radar, that is,
120 $\Delta R = c/2B$ where c denotes the speed of light in vacuum ($\Delta R = 5\text{cm}$ for $B = 3\text{GHz}$).

121 **2.1.2 3D scanning of the radar beam**

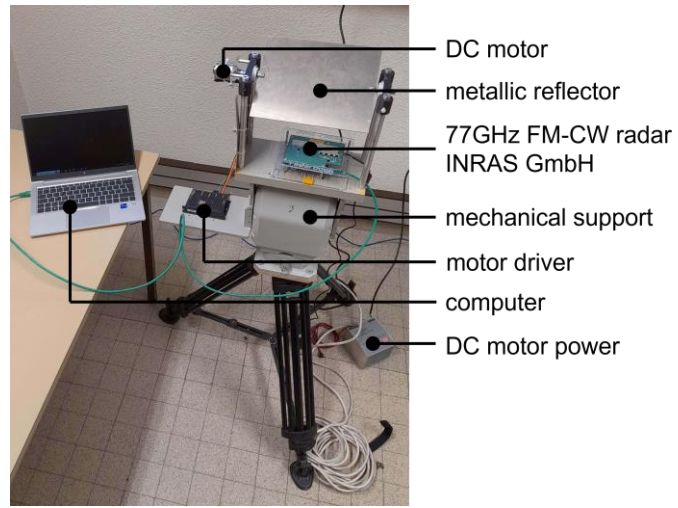
122 Since the off-the-shelf FMCW SIMO radar steers electronically the beam only in a plane, for 3D tracking
123 purpose we perform a mechanical beam scanning in elevation using a rotating reflector to sweep the
124 beam in elevation. As illustrated in Figure 1b, the reflector is a metallic plate placed in front of the radar
125 antennas and rotates at angular frequency ω_α (rad/s). The dimensions of the rectangular plate must be
126 such that most of the radar beam radiated by the T_x antenna is intercepted by the reflector, when its
127 surface faces the antenna or equivalently, when the unit vector \vec{n} normal to the reflector surface is also
128 normal to the radiating surface of the radar ($\alpha=0^\circ$ or 180° in Figure 1b). To meet this requirement, the
129 rectangular plate of 20cm×25cm is placed at the distance z_0 of 15cm in front of the radar antennas.

130



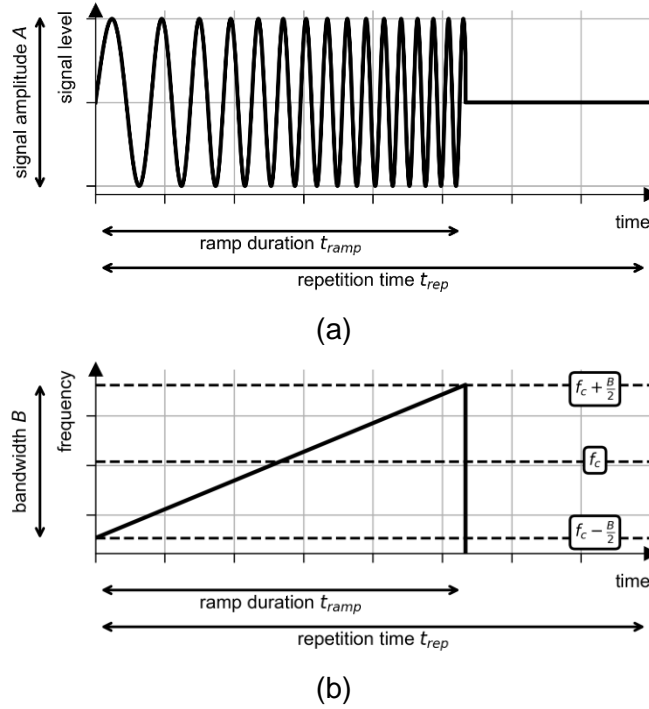
(a)

(b)



(c)

131 Figure 1 – Millimeter-wave radar imaging system: (a) Block diagram of the system used to steer mechanically the
 132 radar beam in elevation and electronically in azimuth; (b) Definition of the azimuth angle φ and elevation angle θ of
 133 the radar beam direction, and of the angle α between the unit vector $-\vec{z}$ of the z-axis and unit vector \vec{n} normal to the
 134 reflector surface; (c) Photo of the millimeter-wave radar imaging system used to track the motion of flying insects.



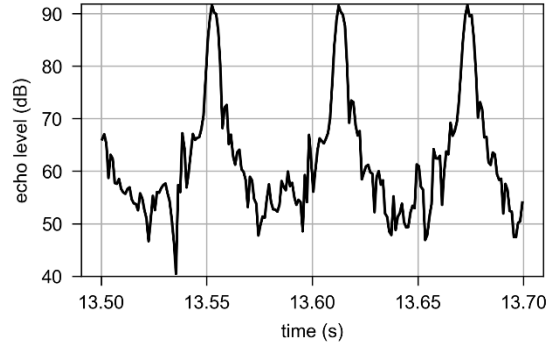
135

136 **Figure 2 – Frequency modulated waveform periodically transmitted by the T_X -antenna of the radar: (a) level and (b)**
 137 **frequency of the waveform as a function of time. f_c and B denote respectively the operating frequency and modulation**
 138 **bandwidth of the transmitted FM signal, called the *sweep*, while t_{rep} designates the period or repetition time, and t_{ramp}**
 139 **is the ramp duration of the (linear) modulation of the sweep. During each period, the signal is transmitted only during**
 140 **the duration t_{ramp} of the ramp.**

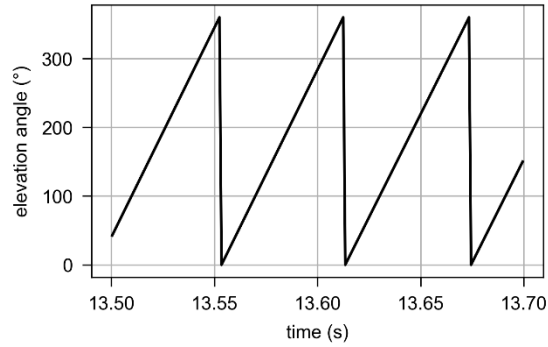
141

142 Let θ and φ denote respectively the elevation and azimuth angles of the radar beam direction (see
 143 Figure 1b). According to the laws of reflection, the elevation angle θ of the radar beam direction is twice
 144 the angle α between the unit vector $-\vec{z}$ of the z-axis and unit vector \vec{n} normal to the reflector surface.
 145 During one full rotation of the reflector, α ranges from 0° to 360° and therefore, each point in the 3D
 146 scene is illuminated twice by the radar beam. As sweeps are sequentially transmitted at times 0 ,
 147 t_{rep} , $2t_{rep}$, $3t_{rep}$, ..., $(N_L-1)t_{rep}$ by the T_X -antenna, the step angle $\Delta\theta$ of beam elevation between two
 148 successive sweep transmissions is given by $2\omega_\alpha t_{rep}$. To prevent blind spots in elevation, the step $\Delta\theta$
 149 must be smaller than the half-power beamwidth (13.2°) of the radar T_X -antenna. To meet this
 150 requirement, we set $t_{rep}=1\text{ms}$ and $\omega_\alpha=500\text{rpm}$, which leads to $\Delta\theta=6^\circ$. Therefore, during 1 second, the
 151 radar beam scans the 3D scene 16.7 times. However, the DC motor used in our experiment to drive the

152 rotation of the reflector does not provide a constant angular rotation speed. Indeed, the standard
153 deviation (over 1024 samples) of the angular frequency is of 45rpm and as a result, during radar
154 measurement the scan rate in elevation ranges from 16 scans/s to 17.5 scans/s. Therefore, the use of
155 the time average for the scan rate to determine the elevation angle of the radar beam direction can
156 result in a large inaccuracy in estimating the 3D location of the targets. To avoid such inaccuracy, the
157 scan rate is estimated over time by deriving the elevation angle of the reflector from the beat frequency
158 spectrum obtained at the radar-to-reflector distance. Such spectrum is displayed in Figure 3a, in which
159 higher peaks of echo level occur periodically at the distance z_0 ($\pm 2\text{cm}$) from the radar radiating surface,
160 that is, when the unit vector \vec{n} normal to the reflector surface is also normal to the radiating surface of
161 the radar ($\alpha=0^\circ$ or 180°). As angular speed is assumed to be constant between two successive peaks,
162 the variation of elevation angle over time can be derived from the time intervals between two peaks and
163 from the knowledge of the rotation direction –clockwise or counterclockwise– of the reflector (see Figure
164 3b). As explained above, the proposed mechanical beamscanning system allows to estimate the range
165 and angle of arrival of a target but does not allow to estimate the speed of a target from a Doppler
166 analysis of the raw radar data. Indeed, estimating the speed from a Doppler analysis requires recording
167 samples along the slow time axis for the same elevation angle which is not achievable using the
168 proposed solution as the elevation angle changes along slow time. From our approach, we estimated
169 the target location in 3D space and computed the instantaneous speed from the location samples
170 through time.



(a)



(b)

171 **Figure 3 – (a) Beat frequency spectrum at the radar-to-reflector distance $z_0=15\text{cm}$ during the rotation of the reflector**
 172 **(higher peaks occur when $\alpha=0$ and 180°); (b) estimated elevation angle of the radar beam as a function of time derived**
 173 **from the time intervals between two successive peaks in the beat frequency spectrum and for a clockwise direction**
 174 **of the reflector rotation (angular speed is assumed to be constant between two successive peaks).**

175 2.1.3 Generation of 3D images from the millimeter-wave radar scanning system

176 From the raw data collected by the R_X -antennas of the radar system, 3D images are generated from
 177 the following step-by-step process illustrated in Figure 4:

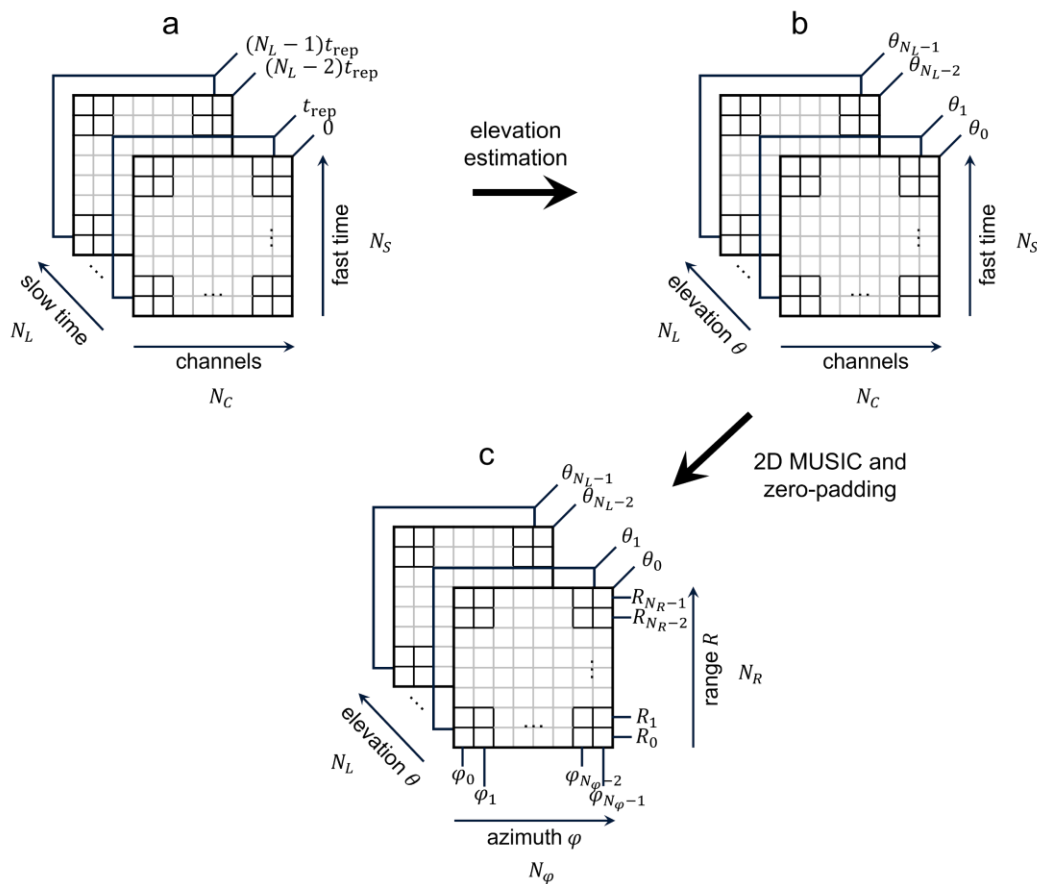
- 178 *i.* At each slow time sample nt_{rep} where $n=0, 1, \dots, N_L-1$, one chirp is transmitted by the $N_{T_X}(=1)$ T_X -
 179 antenna and backscattered by the scene. The signals received by the $N_{R_X}(=16)$ R_X -antennas of
 180 the radar are then digitized and stored in a matrix called the *frame* F_n of dimensions $N_C \times N_S$, where
 181 $N_C=N_{T_X}N_{R_X}$. From such raw data collection obtained at slow time nt_{rep} , each row of the frame is
 182 multiplied by the appropriate calibration complex-valued vector provided by the radar manufacturer
 183 (INRAS, 2023). Frames $F_0, F_2, \dots, F_{N_L-1}$ obtained respectively at slow time samples
 184 $0, t_{\text{rep}}, \dots, (N_L-1)t_{\text{rep}}$ are finally stacked in a matrix of dimensions $N_L \times N_C \times N_S$ (see Figure 4a);

185 *ii.* At each slow time sample nt_{rep} where $n=0, 1, \dots, N_L-1$, the elevation angle θ_n of the radar beam
186 direction is estimated from the beat frequency spectrum, as described in section 2.1.2.
187 The matrix M of dimensions $N_L \times N_C \times N_S$ is then built, as illustrated in Figure 4b;

188 *iii.* Two sampling grids are next built:
189 (1) the *range sampling grid* $R=[R_0, R_1, \dots, R_{N_S-1}]$ where N_S is the number of samples used to
190 digitize the range R and $R_i=i\Delta R$, with $i=0, \dots, N_S-1$, and
191 (2) the *azimuth sampling grid* $\Phi=[\varphi_0, \varphi_1, \dots, \varphi_{N_C-1}]$. To point the radar beam in the azimuth angle
192 φ_k , with $k=0, \dots, N_C-1$, the phase shift $\Delta\phi_k (= 2\pi k/N_C - \pi)$ between two adjacent receiving antennas
193 must be equal to $2\pi \frac{d}{\lambda} \sin(\varphi_k)$, where d is the distance between the antennas and λ is the free-
194 space wavelength at the operating frequency f_c . Therefore, the azimuth angle φ_k in the sampling
195 grid Φ is given by $\arcsin\left(-\frac{\lambda}{2d} + k \frac{1}{N_C} \frac{\lambda}{d}\right)$. To avoid spatial aliasing, this angle must range between -90°
196 and $+90^\circ$ and therefore, the distance d between two antennas must not exceed half-wavelength.
197 As $d=\lambda/2 (=1.95\text{mm})$ for the radar used here in our system, the azimuth angle φ_k equals
198 $\arcsin\left(-1+k \frac{2}{N_C}\right)$, with $k=0, \dots, N_C-1$;

199 *iv.* 2D MUSIC (MULTiple Signal Classification) algorithm reported in (Manokhin et al., 2015) is applied
200 separately to each frame F_n ($n=1, 2, \dots, N_L$) of the matrix M . This discrete source DOA estimation
201 algorithm estimates the so-called *2D-MUSIC score function* for the range and azimuth angles.
202 Each pixel (i,k) in the corresponding 2D-space image of dimension $N_C \times N_S$ contains a *MUSIC score*
203 $P_n[i,k]$ at the range-azimuth (R_i, φ_k) . The zero-padding is next applied by using the padding factors
204 p_R and p_φ for the range and azimuth axes, respectively. Therefore, the padded number $N_{\text{FFT},R}$ for
205 the range samples is given by $2^{\lceil \log_2 N_S \rceil + p_R}$, while the padded number $N_{\text{FFT},\varphi}$ for the azimuth samples
206 is given by $2^{\lceil \log_2 N_C \rceil + p_\varphi}$, where $\lceil \cdot \rceil$ denotes the ceiling function. The number N_φ of samples required
207 to build the MUSIC score function for the azimuth angle is then of $N_{\text{FFT},\varphi}$. To avoid spatial aliasing,

208 negative frequencies of the frequency spectrum for the range are discarded and therefore, the
 209 number N_R of samples required to build the MUSIC score function for the range is only of $N_{FFT,R}/2$.
 210 Finally, the range and azimuth angle in uniformly padded sampling grids are then respectively
 211 given by $R_i = i \frac{N_S}{N_R} \Delta R$ and $\varphi_k = \arcsin\left(-1 + k \frac{2}{N_\varphi}\right)$, where $i=0, \dots, N_R-1$ and $k=0, \dots, N_\varphi-1$. In addition, each
 212 voxel (i, k, n) in the 3D-space matrix of dimension $N_R \times N_\varphi \times N_L$ contains the value of the MUSIC
 213 score $P_n[i, k]$ at the spherical coordinates $(R_i, \varphi_k, \theta_n)$, where $n=0, 1, \dots, N_L-1$ (see Figure 4c). The
 214 size N_{tot} of data recorded during $\Delta t = (N_L-1)t_{rep}$ is then given by $N_R N_\varphi N_L n_0$, where n_0 is the number
 215 of bits used to code each echo level in the pixelized 2D-space image.



216

217 **Figure 4 – Illustration of the generation of the 3D-space radar images from the millimeter-wave radar scanning system:**
 218 **(a) radar data are sorted by increasing slow time; (b) radar data are sorted by increasing elevation angle; (c) 3D-space**
 219 **radar matrix.**

220

221 2.1.4 Electromagnetic clutter mitigation, detection and tracking algorithms

222 A well-known and widely-used detection algorithm in radar image processing is the Constant False
223 Alarm Rate (CFAR) algorithm (Finn and Johnson, 1968). Variations of this algorithm were applied
224 recently for automotive detection using the Area-Based CFAR (Wei et al., 2023), and by us to monitor
225 the sow postural activity from the so-called Cell-Averaging CFAR (Henry et al., 2023).

226 Here, a novel detection algorithm is proposed to detect and locate flying insects in a 3D environment
227 from radar images. This detection algorithm enables both to mitigate the electromagnetic clutter (i.e.,
228 the undesirable radar echoes radar echoes from electromagnetic backscattering of the environment)
229 and to estimate flight path of insects. Let us detail each step of the algorithm illustrated in Figure 5a:

230 *i.* Following section 2.1.3, the 3D-space matrix of dimensions $N_R \times N_\phi \times N_L$ is generated from the
231 beam scanning of the environment in absence of flying insects (see Figure 6a). Each voxel (i, k, n)
232 in the matrix contains the value of the MUSIC score $P_n^{\text{ref}}[i, k]$ at the spherical coordinates $(R_i, \phi_k,$
233 $\theta_n)$, where $R_i = i \frac{N_S}{N_R} \Delta R$, $\phi_k = \arcsin\left(-1 + k \frac{2}{N_C}\right)$ and θ_n is the elevation angle of the radar beam
234 direction derived from step *ii* in section 2.1.3 and $\theta_n - 2\pi \left\lfloor \frac{\theta_n}{2\pi} \right\rfloor$ is the associated principal angle. Let
235 B_m be the set of 2D-space images obtained at elevation angles ranging from $(m-1)\Delta\theta$ to $m\Delta\theta$,
236 with $m=0, 1, \dots, N_\theta-1$, where $N_\theta = 2\pi/\Delta\theta$, and let $\bar{\theta}_m$ be the arithmetic mean of this set (see Figure
237 6b). Then, we build the image \bar{P}_m^{ref} in which the pixel (i, k) contains the arithmetic mean of MUSIC
238 scores at the pixel (i, k) of all images in the set B_m (see Figure 6c). From the stacking of the
239 reference 2D-space images $\bar{P}_0^{\text{ref}}, \bar{P}_1^{\text{ref}}, \dots, \bar{P}_{N_\theta-1}^{\text{ref}}$, the so-called *reference 3D-space image* of
240 dimensions $N_R \times N_\phi \times N_L$ is finally derived;

241 *ii.* The segmentation algorithm illustrated in Figure 5b is applied to the images \bar{P}_m^{ref} (with $m=0, 1, \dots,$
242 $N_\theta-1$) of the reference 3D-space image derived at step *i*, that is, in the absence of flying insects.
243 Each $N_R \times N_\phi$ image (Figure 7a) is segmented by using *isolines* (Figure 7b): along an isoline, the

244 radar echo keeps a constant level (Henry and Aubert, 2019). The calculation of isolines is
 245 adaptive (input parameters of the algorithm are dependent on features of the image to be
 246 segmented). An isoline borders a surface on which the level and position of the highest MUSIC
 247 score is determined (see Figure 7c): if this level is higher than a predefined threshold P_{\min} (e.g.,
 248 $P_{\min}=-47\text{dB}$), we assert that this MUSIC score contributes significantly to the electromagnetic
 249 clutter. Following this criterion, the *reference clutter* contributors are selected in the images \bar{P}_1^{ref} ,
 250 \bar{P}_2^{ref} , ..., $\bar{P}_{N_\theta-1}^{\text{ref}}$ and characterized by their respective azimuth-range locations and MUSIC scores
 251 for N_θ elevation angles;

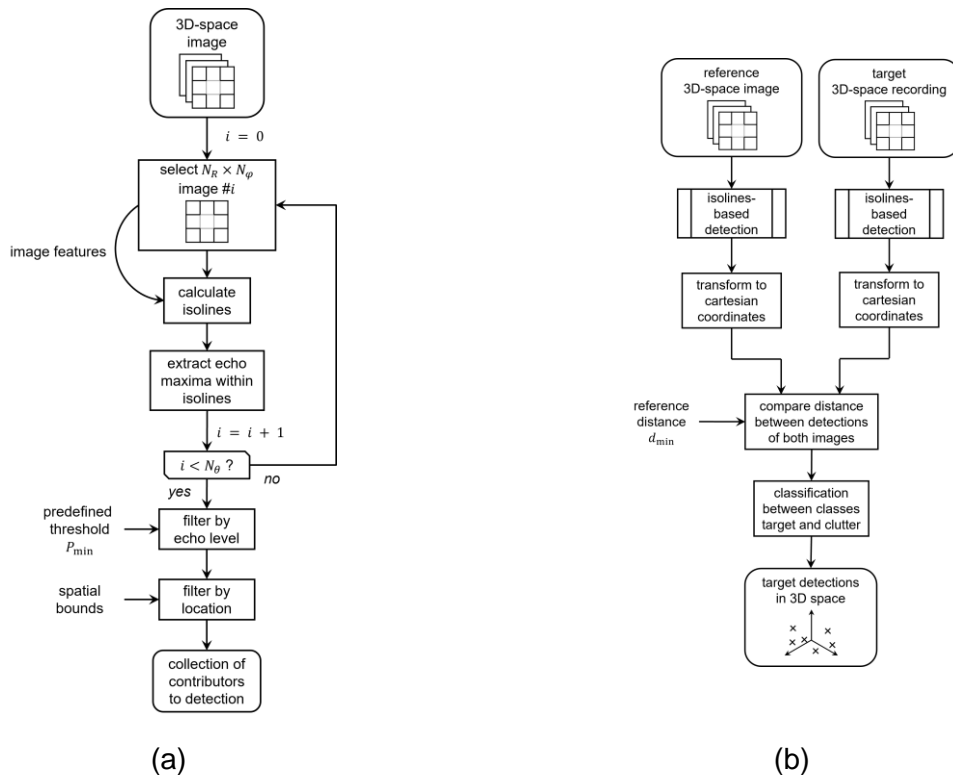
252 *iii.* In the presence of insects, the so-called *target 3D-space matrix* is generated from the beam
 253 scanning of the scene during the measurement time Δt . We apply the segmentation algorithm
 254 based on isolines on each $N_R \times N_\phi$ image derived from the target 3D-space matrix. At this step
 255 of the process, local maxima of MUSIC scores that are higher than the predefined threshold P_{\min}
 256 originate either from the insects to be detected or from the electromagnetic clutter. They form a
 257 set of *unclassified* contributors, that are characterized by their respective range-azimuth-
 258 elevation coordinates and MUSIC scores. Range-azimuth-elevation coordinates of unclassified
 259 contributors are finally mapped into Cartesian coordinates;

260 To decide if an unclassified contributor originates from an insect or from the electromagnetic
 261 clutter, we calculate the distances between this contributor and those detected in the reference
 262 image at step *ii*. If at least one distance is below the pre-defined d_{\min} threshold, then we assert
 263 that the contributor is brought by the electromagnetic clutter, otherwise it originates from the
 264 insect (Figure 8c). Following this criterion, position of the insect is determined over time (Figure
 265 8d). The threshold distance d_{\min} can be derived from the reference 3D-space image in absence
 266 of insects. For this purpose, the aforementioned segmentation based on isolines is applied on
 267 each 2D-space image i with $i=0, \dots, N_L-1$ of the reference recording and provides a set of $N_{\text{iso},i}$
 268 isolines. Then, the barycenter of each isoline is computed and stored. We obtain a set of

269 barycenter $B_{k,i}$ where $k=0,\dots,N_{iso,i}-1$ and $i=0,\dots,N_L-1$. The shortest Euclidean distance from the
270 set of distances $|B_{k,i}-B_{l,j}|$ for $(l,j)\in[0,\dots,N_{iso,i}-1]\times[0,\dots,N_L-1]-(k,i)$ is then determined and stored
271 for each $k=0,\dots,N_{iso,i}-1$ and $i=0,\dots,N_L-1$ thus yielding a set of size $N_{iso,0}+N_{iso,1}+\dots+N_{iso,N_L-1}$. The
272 longest distance of this set is named the *reference distance* and is denoted by d_{ref} (here,
273 $d_{ref}=15\text{cm}$) [remark : In (Dedic et al., 2023) we proposed a clutter mitigation algorithm in which
274 the classification is carried out by calculating the distances between each point of the isoline
275 while here, only the distance between the level of highest echo within the isoline and contributor
276 is computed. This results in a significant reduction in the computation time];

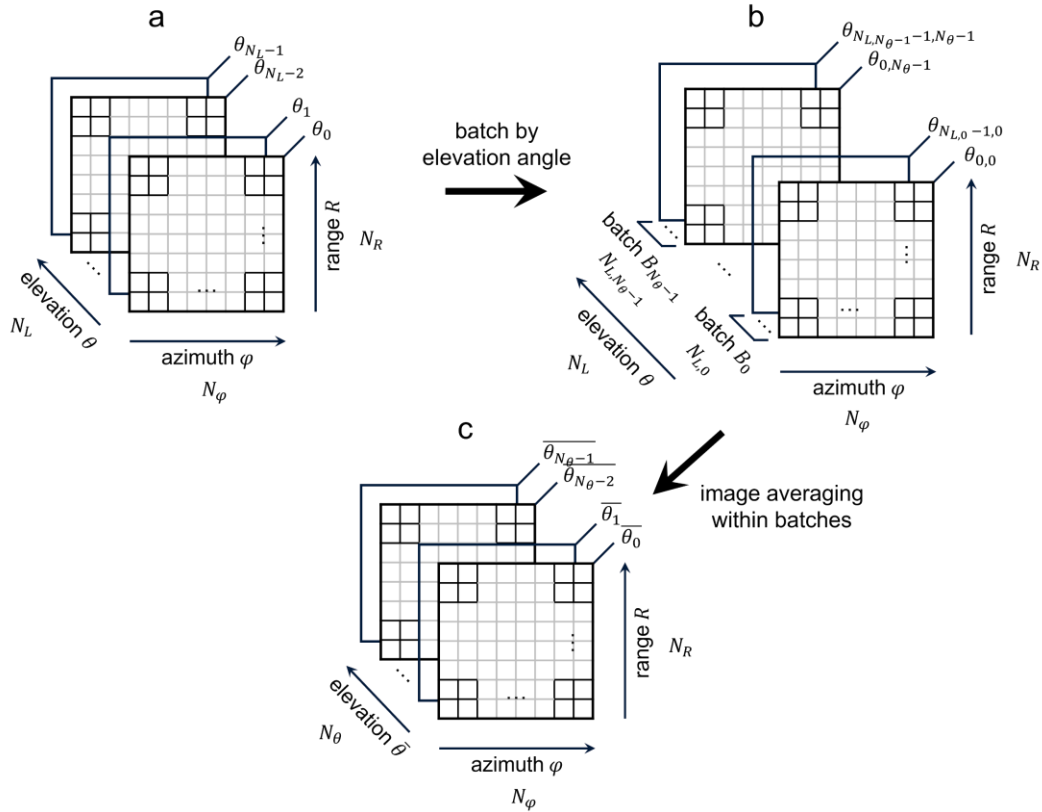
277 *iv.* A simple spatial smoothing method is devised to build the target tracks from the set of target
278 detections. Each detection $(R_{target,k}, \varphi_{target,k}, \theta_{target,k})$ of the set of target detections is labeled
279 with a timestamp $t_{target,k}$ at the elevation angle $\theta_{target,k}$ such that $t_{target,k} = \left\lfloor \frac{\theta_{target,k}}{2\pi} \right\rfloor \frac{1}{f_{scan}}$, where
280 f_{scan} ($=16.7$ scans/s) is the scan rate. Thus, detections for which the elevation angle is closer
281 than 2π may have the same associated timestamp. Then the set of target detections is sorted
282 by increasing timestamps. We assume that only one target is present in the scanned scene so
283 we assume no ambiguous track assignments to resolve. For each timestamp, we compute the
284 barycenter of the sub-sets of detections for which the timestamp is identical so as to obtain only
285 one detection per timestamp. The so-called *target track* is then the obtained set of barycenters
286 sorted by increasing timestamp.

287



288
289

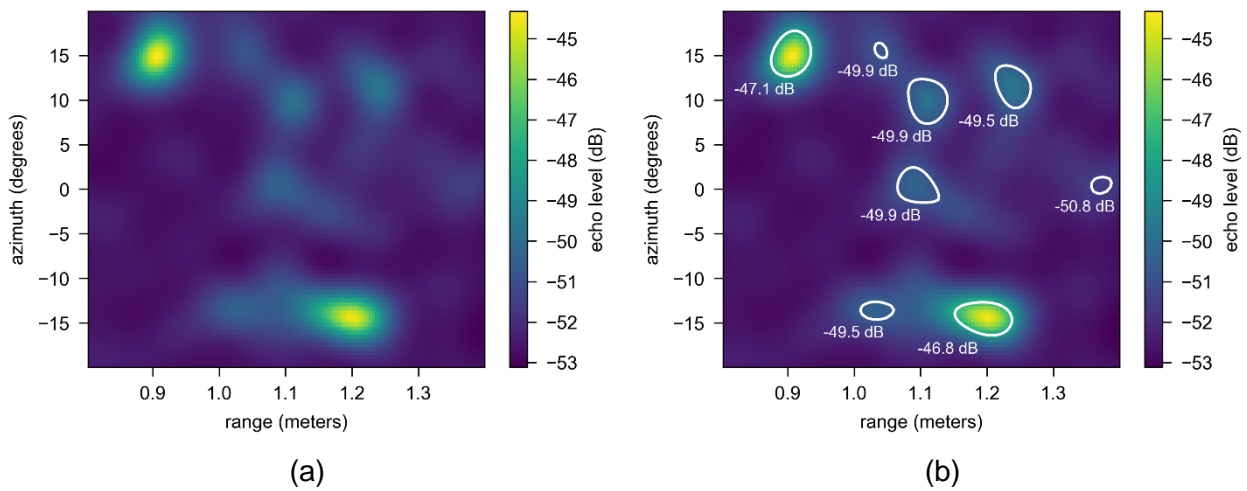
Figure 5 – Block diagrams of the detection algorithm applied on a 3D-space image: (a) clutter mitigation process, (b) isolines-based detection subroutine to extract maxima from a 3D-space image using segmentation by isolines.

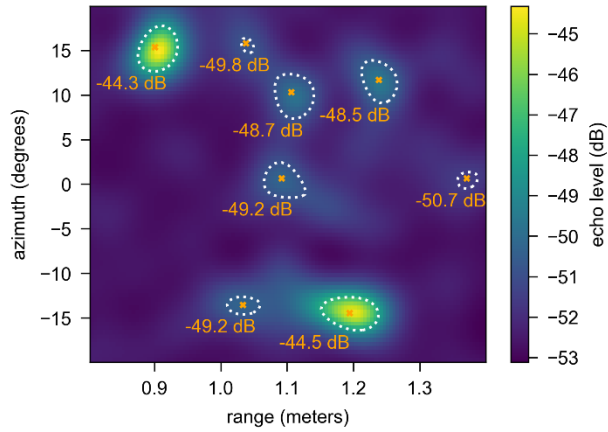


290

291 **Figure 6 – Derivation of the reference 3D-space image from the 3D-space recording matrix of the environment in**
 292 **absence of flying insects: (a) Reference 3D-space radar recording matrix, (b) reference 3D-space radar recording**
 293 **matrix sorted by increasing batch rank of elevation angles and (c) reference 3D-space image.**

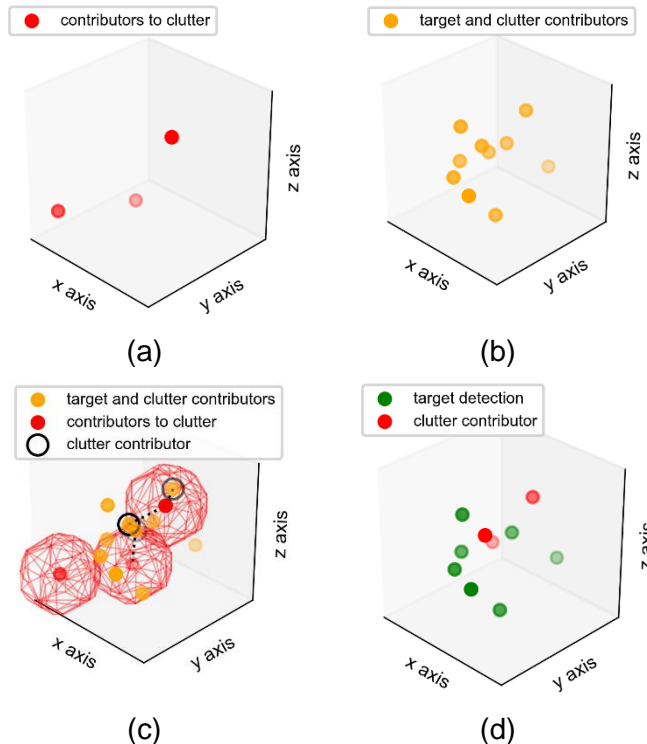
294





(c)

295 Figure 7 – Illustration of the calculation of isolines applied to a 2D image: (a) range-azimuth mapping of MUSIC scores
 296 (namely the *MUSIC score function*), (b) calculated isolines (solid, white) with associated isoline levels (white)
 297 superimposed on the MUSIC score function, (c) derived detection points (solid, orange) with associated detection
 298 MUSIC score (in dB) (solid, orange) and isolines (dotted, white) superimposed on the MUSIC score function.

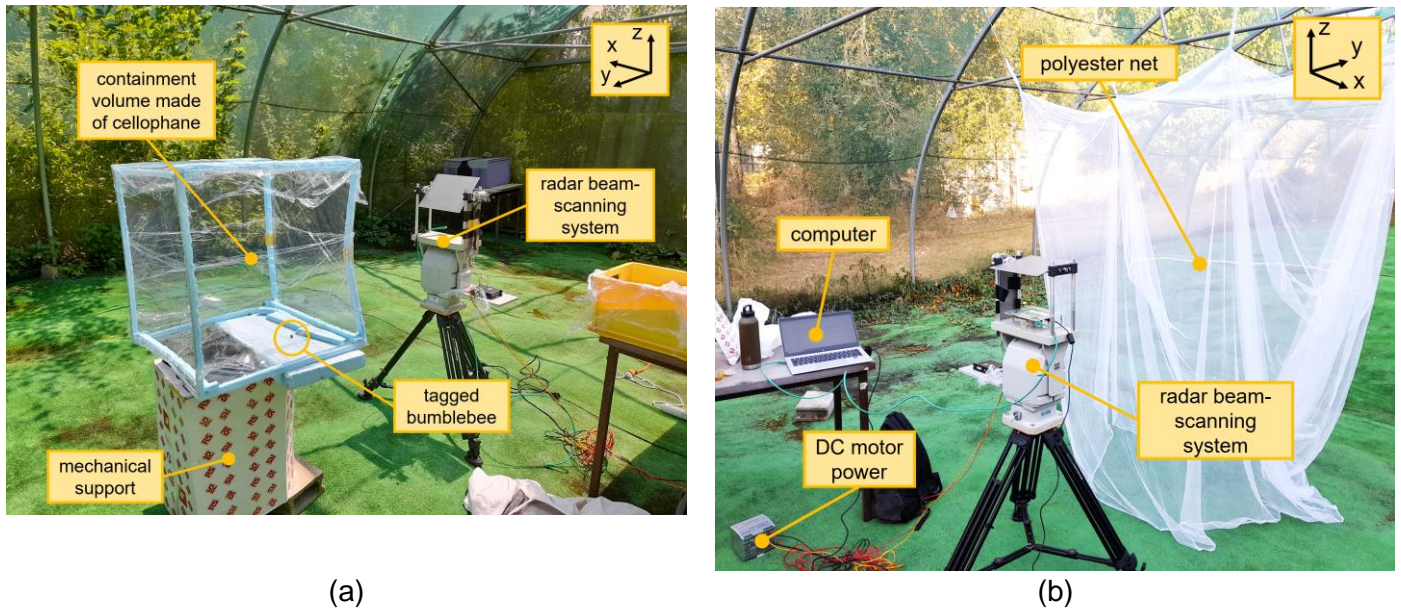


299 Figure 8 – Illustration of the process to mitigate the electromagnetic clutter: (a) location (in red) of contributors to the
 300 clutter in the reference image; (b) locations (in orange) of unclassified contributors that originate either from an insect
 301 or from the electromagnetic clutter; (c) location of contributors to clutter of Figure 8a (in red) of unclassified
 302 contributors of Figure 8b (in orange) and of contributors selected as originating from the electromagnetic clutter (in
 303 black, solid). The contributors to the clutter are such that their distance to the closest reference clutter contributor
 304 (in black, dotted) is included in the volume of the red meshed polygon shown in Figure 8(c); (d) estimated location of
 305 the insect (in green) and of the contributors to electromagnetic clutter (in red).

306 **2.2 3D motion tracking of bumblebees**

307 **2.2.1 Experimental setup**

308 The proposed radar detection system and algorithm were applied to track bumblebees (*Bombus*
309 *terrestris*) from commercially obtained hives (Koppert, The Netherlands). The measurements were
310 performed in a 20×10×4 m³ outside flight tent (Figure 9a) at the experimental apiary of the CRCA-CBI
311 (Toulouse, France). We applied the new detection algorithm based on the clutter mitigation technique
312 described in Section 2.1.4 and we increased the electromagnetic reflectivity of the bumblebees by
313 equipping them with a small hollow aluminum cylinder of 1.5 cm long, 2.0 mm in diameter and 100 μm
314 of thickness. The simulated Radar Cross-Section of the cylinder at the radar working frequency (77GHz)
315 is of -31dBsm. The weight of the cylinder was about 50mg, that is, only 13% of the average weight of a
316 bumblebee (400mg). Preliminary detection results showed that 3D motion of this cylinder inside the two
317 flight cages can be tracked by the radar system (see Supplementary materials, Figure S2). Here we
318 constrained the movements of the bumblebees within the radar detection volume by using flight cages
319 made of materials (thin plastic films foam and polyester) weakly reflecting to millimeter-waves. We used
320 two flight cages with different volumes: in the Setup #1, the cuboid cage of 0.22m³ was made of
321 cellophane for the cube faces and foam for the edges (see Figure 9a), while in Setup #2 the cage was
322 made of polyester net which delimits the larger volume of 1.5m³ (see Figure 9b). For comparison
323 purposes, 2D video recordings of the detection volume have been made during the radar scanning by
324 using a single video camera.



(a)

(b)

325 **Figure 9 – Photos of the experimental setup: (a) setup #1; (b) setup #2. The volume that restrained the movements of**
 326 **the insect was placed in front of the radar beam-scanning system. Cartesian (x, y, z) coordinates are specified in**
 327 **insert.**

328 2.2.2 Measurement protocol

329 The radar tracking system was used for single target tracking, meaning that only one bumblebee was
 330 tracked at a time. All tested bumblebees came from the same colony. Before the measurements, bees
 331 were cold-anaesthetized at -12°C and equipped with metallic cylinder attached to their thorax using
 332 cyanoacrylate gel glue (Loctite SuperGlue 3). We selected rather large individuals in order to reduce
 333 the mass ratio between the cylinder and the bee. As described in 2.1.4, the calibration of the
 334 experimental setup was performed by scanning the radar beam in the flight cage in absence of insects.
 335 A bee was then introduced in Setup #1 or Setup #2. The motion of one bee (bee #1) was tracked in
 336 Setup #1 on 2023-06-30, and that of two other bees (bee #2 and bee #3), one after the other, in Setup
 337 #2 on 2023-08-23. Radar measurements were carried out for a total observation time of about 37
 338 minutes (362s for bee #1, 1167s for bee #2, 691s for bee #3) under a hot sunny morning for both setups.
 339 After the collection of radar data and video recordings, bees returned to their colony nest.

340 2.2.3 Data analysis

341 Five features (see Table 1) were annotated manually for all video recordings and considered as ground-
 342 truth (see Supplementary materials Figure S1). At each given recorded moment, the location of the bee

343 in Cartesian coordinates (x_v, y_v, z_v) was annotated relatively to the origin placed at the center of the
 344 rotating axis of the beam scanning system. Therefore, a bee located at the bottom left front corner of
 345 the confinement volume would be assigned the location $(x_v=0, y_v=0, z_v=0)$. A bee located close to
 346 computed reference clutter contributors would be assigned $c_v=1$. The bee's activity m_v was also
 347 annotated. For instance, a bee flying in the confinement volume would be assigned the activity $m_v=1$.
 348 For each video, we identified the 3D position of the bee relative to the radar system, the proximity of the
 349 bee to highly cluttered areas, and the activity of the bee. All the recorded features were binary features
 350 and Pearson correlation matrices were computed. Automated analyses (described in Section 2.1.4)
 351 were used to extract 3D tracks from the radar data. Instantaneous speed was numerically estimated
 352 from the 3D tracks. To compare bee tracks from video recordings with those from radar recordings,
 353 binary classifications were applied on the positional features and instantaneous speed extracted from
 354 radar recordings. Confusion matrices were then evaluated for each feature and conclusions were drawn
 355 on the accuracy of the radar tracking system. Statistical analyses were performed using Python 3.9.0
 356 with statistical packages NumPy 1.23.5, SciPy 1.9.3, SciKit-Learn 1.3.0. Graphical representations were
 357 rendered using Matplotlib 3.6.3.

358 **Table 1 - Description of the features annotated from the manual analysis of the video recordings. The reference clutter**
 359 **contributors are extracted from the reference 3D-space image.**

feature name	type	definition	feature values	
			0	1
x_v	binary categorical	Cartesian position of the bee relatively to the radar system	left	right
y_v			close	far
z_v			low	high
m_v		bee's activity	moving slow	moving fast
c_v		proximity to reference clutter contributors	far	close

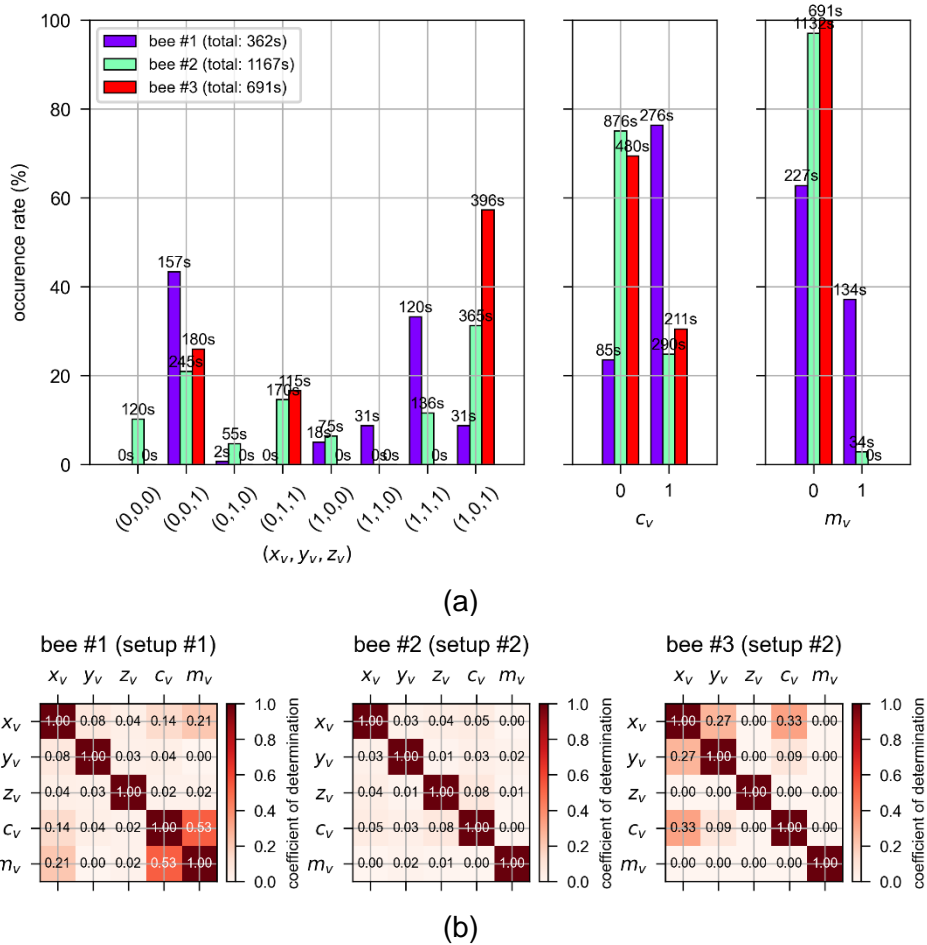
360

361 **3 Results**

362 **3.1 Video analyses**

363 Annotated features statistics are shown in Figure 10. In setup #1, bee #1 was in cluttered areas (mostly
 364 corners of the confinement box) during 277s out of the 362s (76%) whereas in setup #2, bees #2 and

365 #3 were in cluttered areas only during 120s out of the 2,336s (5.1%). This is because less
 366 electromagnetic clutter contributors per unit of volume was generated in setup #2 compared with setup
 367 #1. Moreover, from Figure 10b, the high correlation between the features m_v (activity of bees) and c_v
 368 (proximity to highly cluttered areas) (coefficient of determination: $R^2=0.53$) reflects the fact that bee #1
 369 was often not moving while being in cluttered areas of the scene (mostly corners). From Figure 10a, the
 370 bees spent most of their time (>60%) in the upper part ($z_v=1$) of the confinement volume in both
 371 experimental setups and were mostly moving slowly ($m_v=0$) inside the confinement volume.

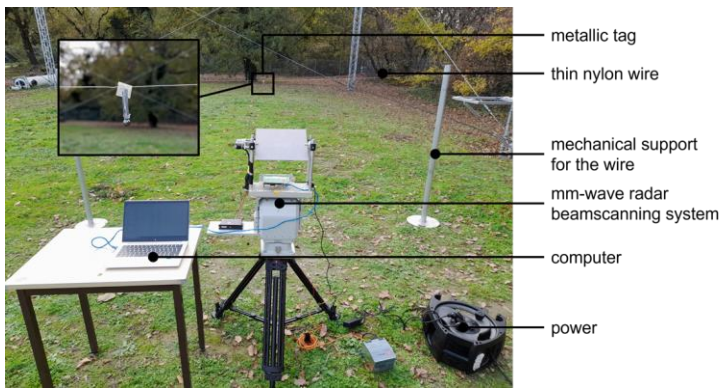


372 **Figure 10 – Statistics of the binary features collected from video recordings: (a) Occurrence rate of the annotated**
 373 **features values for the three tracked bees (bees #1, #2 and #3); (b) Coefficient of determination between all the**
 374 **annotated features for the three tracked bees. See details of annotated features in Table 1.**

375 **3.2 Radar analyses**

376 **3.2.1 Estimation of the detection volume of the radar detection system**

377 The estimation accuracy of the target location provided by the detection algorithm proposed in section
378 2.1.4 is defined as the standard deviation of the 3D distribution of estimated locations of stationary
379 targets. The distribution is here obtained from $N_m (=500)$ successive 3D radar scans of the scene in
380 which the stationary target is placed. Two small targets are used separately in the experimental
381 environment shown in Figure 13a: a small 5mm-diameter metallic ball (target #1, see Figure 11b) having
382 a Radar Cross Section (-47dBsm) close to that of a bumblebee (*B. terrestris*), and a 5mm-diameter
383 metallic ball glued to a 2cm-long metallic cylinder (target #2, Figure 11c), which models the radar
384 signature of a bumblebee equipped with a small cylinder tag or antenna placed vertically on its thorax.
385 The estimation accuracy of the detection algorithm is computed from the $N_p=30$ target locations
386 displayed in Figure 11d.



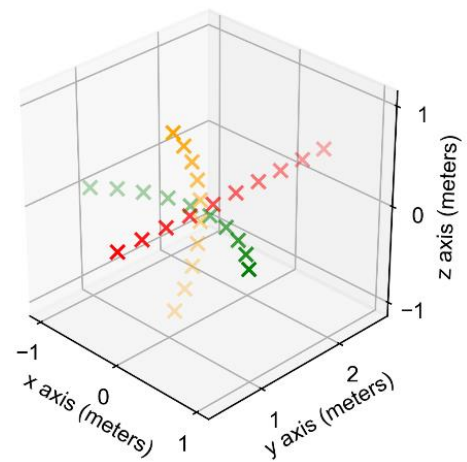
(a)



(b)



(c)

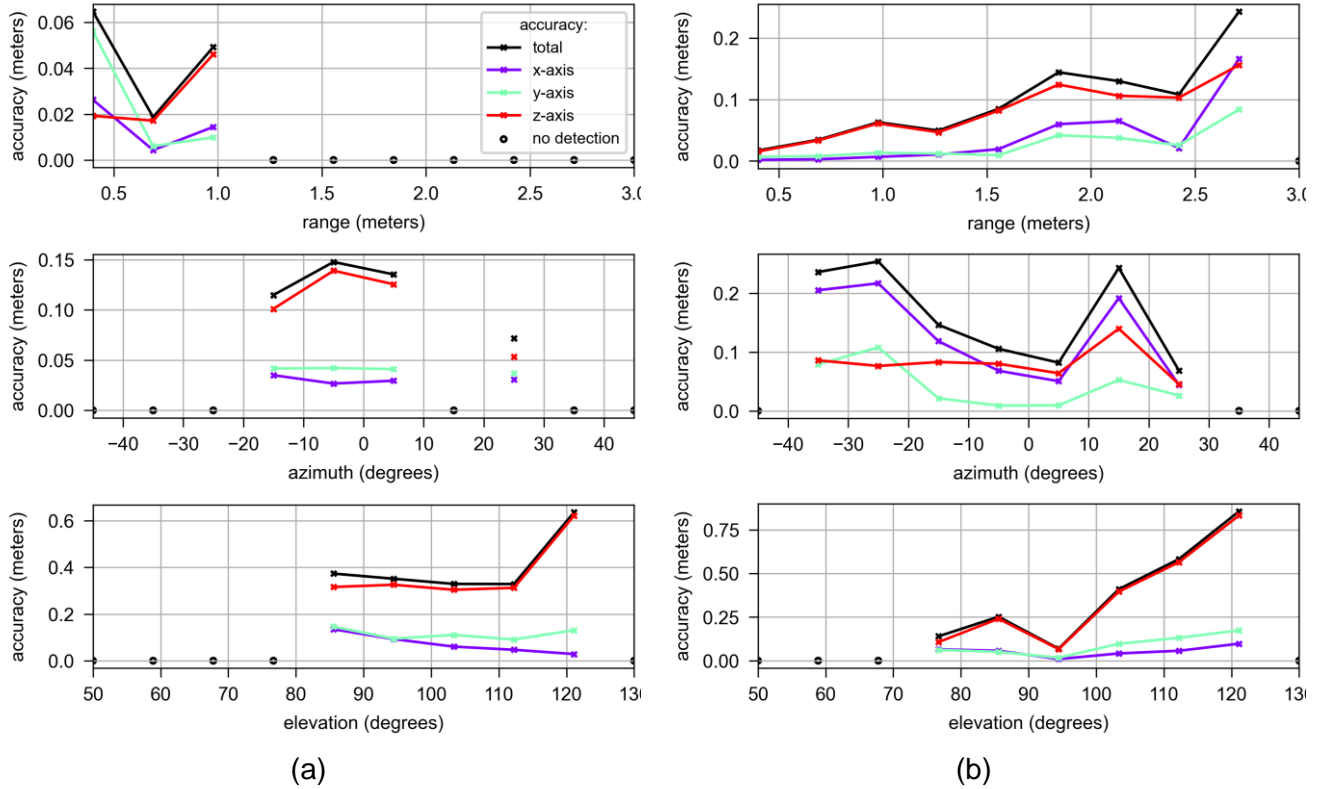


(d)

387

388 Figure 11 – (a) photo of the experimental setup to evaluate the estimation accuracy of target location from mm-wave
389 imaging system; (b) photo of the 5mm-diameter metallic ball (target #1), (c) photo of the 5mm-diameter metallic ball
390 glued to a 2cm-long metallic cylinder (target #2), (d) target locations chosen to determine the estimation accuracy of
391 the target location. A total of $N_p=30$ different target locations were selected: 10 different radar-to-target distances R
392 ranging from 0.4m to $R=3.0$ m with $\varphi=0^\circ$ and $\theta=90^\circ$ (red crosses); 10 azimuth angles φ ranging from -45° to 45° with
393 $R=1.4$ m and $\theta=90^\circ$ (green crosses); and 10 elevation angles θ ranging from 50° to 130° with $R=1.4$ m and $\varphi=0^\circ$ (orange
394 crosses).

395 The estimated accuracies on the range, elevation and azimuth of targets for N_p tested locations are
396 shown in Figure 11d. The target #2 (metallic ball glued with metallic cylinder) was detected in many
397 more (21/30) tested locations than the target #1 (only metallic ball) (12/30). We defined the detection
398 volume of the detection system as the volume in which the uncertainty on the target location was lower
399 than a predefined threshold. From our tests, we could infer that the detection volume in which the
400 location uncertainty did not exceed 30cm is of 0.19m^3 for the target #1 and of 5.25m^3 for the target #2.
401 The target detection rate (the ratio between the total number of target detections and the total number
402 of observable detections) was found to be on average 78% for target #1 and 67% for target #2. The
403 absence of target detection in some 3D frames may be explained by the fact that the radar beam
404 scanned in elevation is pointed towards the static target at a different elevation angle in each 3D frame
405 (see section 2.1.2). The obtained detection volume of the proposed detection system did not enable the
406 system to track an insect in 3D over large spatial scales (hundreds of meters) but may be used to track
407 an insect in 3D in smaller volumes which is already interesting from an ethological point-of-view to study
408 the insect navigational behavior (see Introduction).



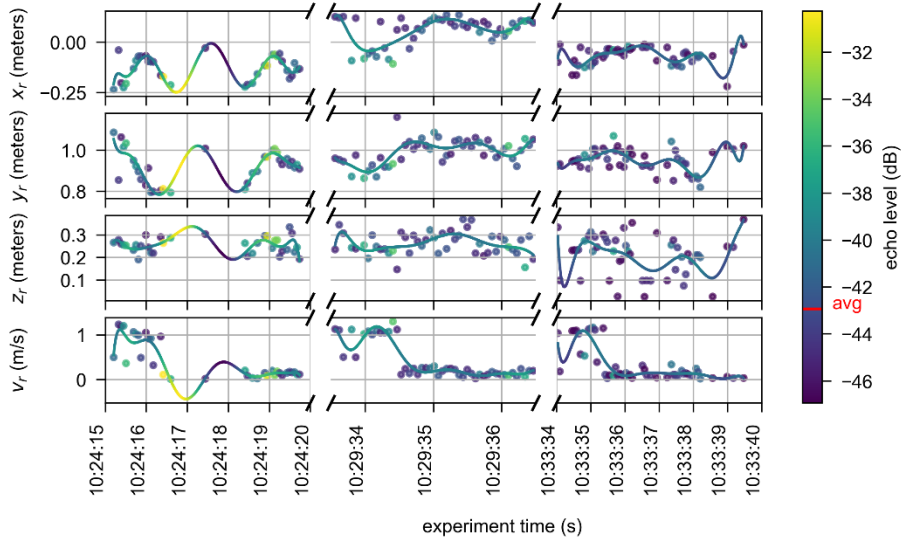
409 **Figure 12 – Estimation accuracy of the detection system for target locations specified in Figure 11a: for the target #1**
 410 **(only metallic ball) (a) and for the target #2 (metallic ball glued to metallic cylinder) (b). For each target, the estimated**
 411 **accuracy is given for the $N_{p,R}$ tested range locations (top row), for the $N_{p,\varphi}$ tested azimuth locations (middle row) and**
 412 **for the $N_{p,\theta}$ tested elevation locations (bottom row). The estimated accuracy (total error) is computed for the Euclidean**
 413 **norm of the error along x-axis, the error along y-axis and the error along z-axis. The accuracy estimation for which**
 414 **the detection rate is lower than 10% is indicated as “no detection” in the figures.**

415 3.2.2 3D tracking of bumblebees

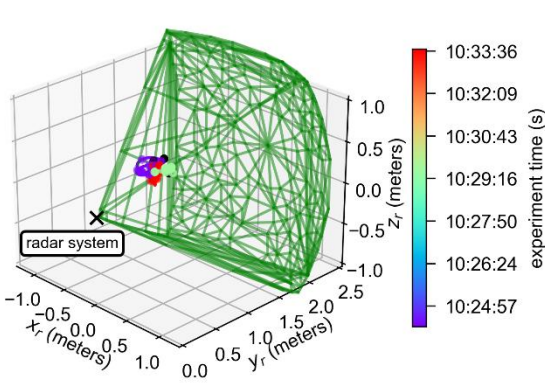
416 3D tracks of bees were extracted from the radar system recordings using the methods described in
 417 Section 2 and are displayed in Figure 13. The origin of the spatial representations of estimated flight
 418 path is set at the center of the rotating axis of the radar beam-scanning system. In Figure 13a, (x_r, y_r, z_r)
 419 denote the estimated Cartesian coordinates of the bee derived from the radar system and v_r denotes
 420 the instantaneous speed of the bee estimated from the radar detection system. The polynomial
 421 interpolation of 3D motion tracks was reconstructed from the time-domain collection of bee detections
 422 shown in Figure 13a. Statistics for the bee coordinates derived from the radar detection algorithm are
 423 given in Figure 14. The average estimated speed of detected bees was of 0.33m/s for bee #1, 0.18m/s
 424 for bee #2, 0.10m/s for bee #3. These results are consistent with those obtained from video recordings
 425 (Figure 10). Moreover, we observed that the distances traveled by bee #1 are smaller than those

426 traveled by bee #2 and bee #3. This is explained by the fact that bee #1 was inside a smaller confinement
427 volume than that of bees #2 and #3. The maximum detection range of bees was of 1.77m.

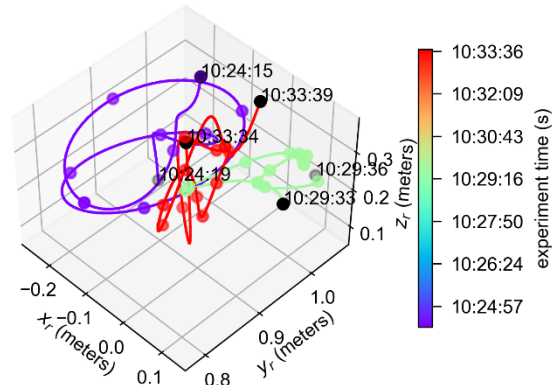
428 To estimate the quality of the 3D tracks, we defined the bee detection rate as the ratio between the total
429 number of bee detections in our dataset and the total number of observable detections. The total number
430 of observable detections provided by the radar system is the product between the scan rate of the radar
431 system (16.7 scans/s) and the recording time of a given bee. For instance, there were 6,045 observable
432 detections for bee #1. The resulting estimated detection rates were of 10% (617/6,045) for bee #1,
433 18% (3,520/19,489) for bee #2, and 13% (1,464/11,540) for bee #3. These rates were low because
434 they are computed with respect to all observable detections, including those obtained when bees were
435 flying near objects in the environment that are highly reflective to electromagnetic waves. In these
436 situations, the radar echo of bees is completely masked by that of these objects and therefore, bees
437 cannot be detected by the radar system. If we remove such well-known masking situations from
438 observable detections, more realistic detection rates were found. They were found to be of
439 43% (617/1,420) for bee #1, 24% (3,520/14,629) for bee #2, 18% (1,464/8,016) for bee #3. These
440 detection rates are still small compared to the average detection rate (67%) for the static target #2
441 (metallic ball glued with metallic cylinder) used in section 3.2.1. Some missing detections may be
442 attributed to time-dependent electromagnetic clutter (e.g. movement of the cage surfaces during the
443 experiments) that is not possible to mitigate (further discussed in section 4.7) and others may be
444 attributed to the changing orientation of the metallic tag (and thus its changing reflectivity) while the bee
445 is moving inside the cage.



(a)

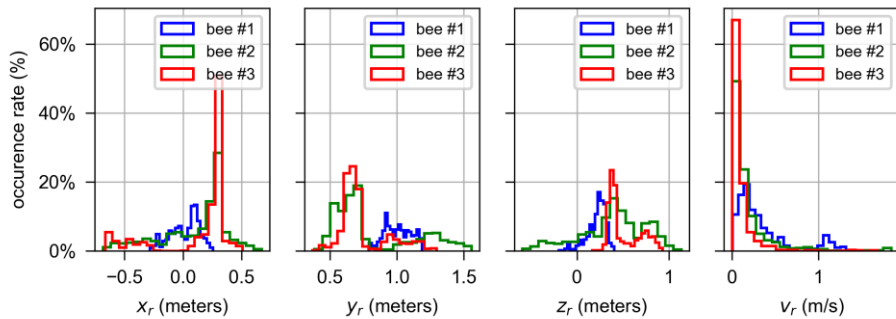


(b)



(c)

446 **Figure 13 - 3D motion tracks of a bee (bee #1): (a) Estimated spatial coordinates x_r , y_r , z_r and speed v_r of the bee as a**
 447 **function of time; (b) Representation of the reconstructed 3D flight path (from pink to red). The location of the radar**
 448 **system is shown by the black cross. The radar detection volume (derived from Figure 12) is displayed as a green**
 449 **meshed polygon; (c) Detailed view of the reconstructed 3D flight path.**



450

451 **Figure 14 – Statistics of the bee location estimated from the radar detection system: (a) bee #1; (b) bee #2 and (c) bee**
 452 **#3.**

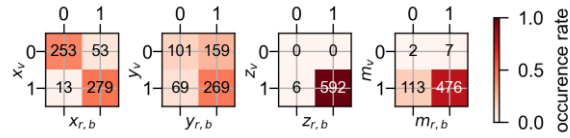
453 **3.3 Validation of 3D motion tracks obtained from the radar system**

454 To compare detections obtained from the radar recordings and those extracted from the video
 455 recordings, the continuous features (x_r, y_r, z_r, v_r) were transformed in binary categorical features ($x_{r,b},$
 456 $y_{r,b}, z_{r,b}, m_{r,b}$). The binary classification rules were derived from the ground-truth measurement of the
 457 barycenter of the confinement volume given in Table 2. Classification accuracy results are shown in
 458 Figure 15. The spatial coordinates of bee #1 have been correctly estimated by the radar system in 90%
 459 of the target detections along the x axis and in 64% of the target detections along the y axis. The features
 460 $z_{r,b}$ and $m_{r,b}$ have been classified correctly in more than 95% of the occurrences. However, the collected
 461 data along the variables z and m was largely imbalanced and thus measuring the classification accuracy
 462 did not reflect classification performance of the smaller-sized class (e.g., class $z=0$ for bee #1). The
 463 spatial distribution of the reference clutter contributors for both setups is given in Figure 16. The large
 464 occurrence peak observed around $x_r=0.0m$ in the distribution of x_r reflects the electromagnetic clutter
 465 generated by the portion of the confinement volume that faced the radar system.

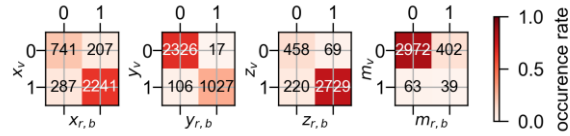
466 **Table 2 - Classification rules for the two experimental setups (#1 and #2) (see Table 1 for features definition).**

values	$x_{r,b}$	$y_{r,b}$	$z_{r,b}$	$m_{r,b}$
setup #1 – cellophane box				
0	$x_r < 0.02m$	$y_r < 0.93m$	$z_r < -0.10m$	$v_r < 0.10m/s$
1	$x_r \geq 0.02m$	$y_r \geq 0.93m$	$z_r \geq -0.10m$	$v_r \geq 0.10m/s$
setup #2 – polyester net				
0	$x_r < 0.00m$	$y_r < 0.93m$	$z_r < 0.10m$	$v_r < 0.35m/s$
1	$x_r \geq 0.00m$	$y_r \geq 0.93m$	$z_r \geq 0.10m$	$v_r \geq 0.35m/s$

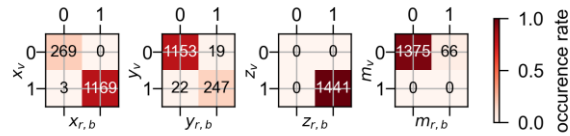
467



(a)

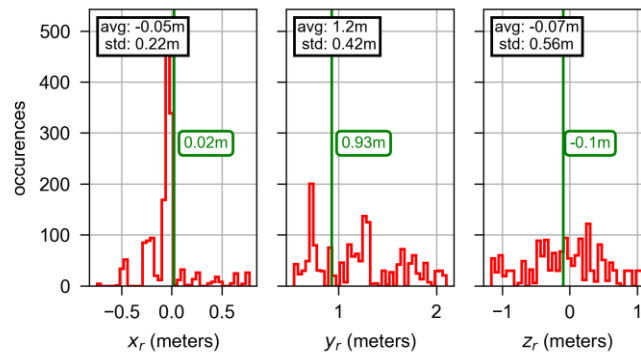


(b)

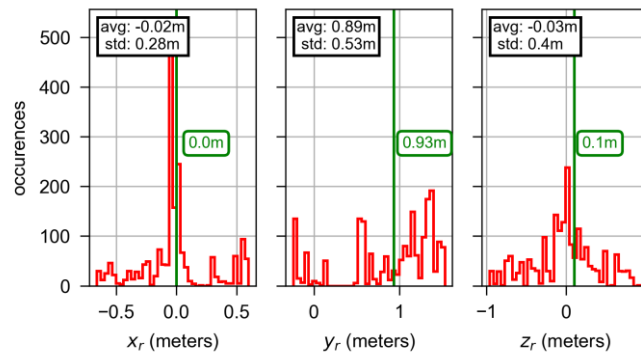


(c)

468 Figure 15 - Confusion matrices for each recorded feature for: (a) bee #1, (b) bee #2, and (c) bee #3.



(a)



(b)

469 Figure 16 - Spatial distribution of reference clutter contributors obtained from the clutter mitigation process (step *ii*,
 470 section 2.1.4): (a) for setup #1, (b) for setup #2. Statistical distributions along the x, y, and z axes are represented in red and the thresholds for classification are represented in green.
 471

472 **3.4 Using a network of multiple radar systems to increase detection volume**

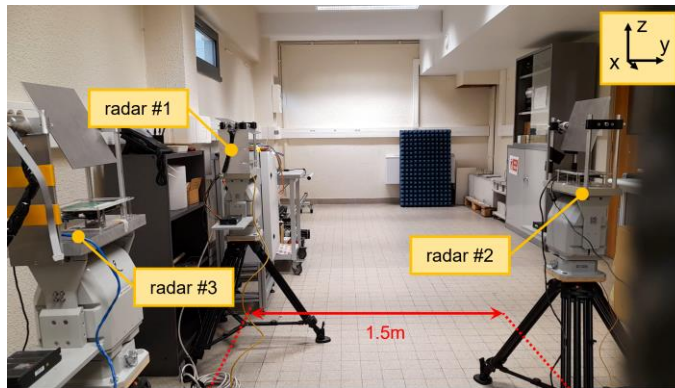
473 Increasing the detection volume can be performed by using multiple radar imaging systems, each
474 illuminating a different region of the environment. To demonstrate this assertion, we moved a metallic
475 target in front of three radar beam-scanning systems shown in Figure 17. The target was a metallic
476 (aluminium) cylinder of 2cm long and 3mm wide, and was attached to a nylon wire, which in turn was
477 attached to a rod. We moved manually this target in front of the 3 radars along x-axis back-and-forth,
478 while the imaging systems scanned simultaneously the scene. The ground-truth locations of the radar
479 relatively to the chosen origin of the setup were measured (see Table 3) with measurement uncertainties
480 of 1cm for distances and 1° for angles. The total detection volume of the proposed radar beam scanning
481 systems network in which the target used in section 3.3 is detected accurately (that is, with estimated
482 accuracy detailed in Figure 12) is found to be 11.1m³. We applied the tracking process described in
483 section 2.1.4 for the radar recordings collected by the three imaging systems. We assumed that the
484 three radar beam scanners were synchronously collecting radar data. A unique joint target track was
485 generated by joining the sets of target detections collected by each radar system (#1, #2 and #3) and
486 sorting by increasing timestamp. We observed that the moving target is successfully tracked during the
487 entire duration of the radar recordings (see Figure 18b).

488 **Table 3 - Configuration of the setup using identical 3 radar beam-scanning systems. The coordinate system is defined**
489 **in Figure 20.**

490

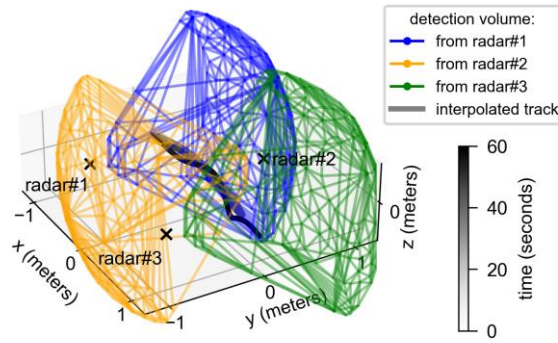
radar	x (m)	y (m)	z (m)
radar #1	-0.75	-0.75	0
radar #2	0	0.75	0
radar #3	0.75	-0.75	0

491

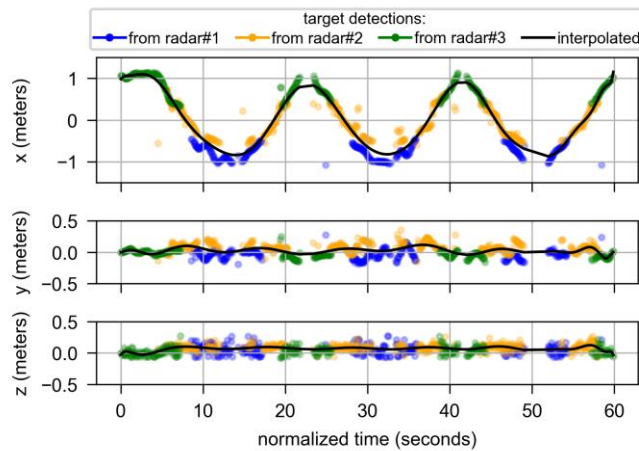


492

493 Figure 17 – Photo of set up with three identical radar beam-scanning systems (radar #1, radar #2 and radar #3).



(a)



(b)

494

495 **Figure 18 – Estimation of the spatial coordinates of a small target (metallic cylinder of 2cm long and 3mm wide) moving**
 496 **back-and-forth along x-axis from 3 radar imaging systems: (a) representation of the 3 detection volumes brought by**
 497 **each radar system (the joint detection volume is of 3.2m³); (b) estimated spatial coordinates x, y, z of the target as a**
 498 **function of time (detections of radar #1 are in blue, of radar #2 are in orange, and of radar #3 are in green and the**
 499 **estimated spatial coordinates of the associated polynomial interpolation is shown in black).**

500 4 Discussion

501 We demonstrated that mm-wave radar technology can be used to track the motion of individual flying
 502 insects with high resolution. A single mm-wave FM-CW radar sensor can be used for such tracking in a
 503 detection volume of 5.3m³ (up to a radar-to-target distance of 2.6m). From ground-truth video validation,
 504 3D tracks obtained from the radar sensor were correct in 82% of the time. Our approach is thus robust
 505 and holds many promises for future behavioral research on flying insects in the field as it is low cost,
 506 transportable, insensitive to light conditions, requires one sensor for resolving 3D, can track through
 507 certain electromagnetic clutter, may eventually track several insects simultaneously, and can be

508 duplicated and combined to increase tracking volumes. Tracking with mm-wave radars is therefore
509 potentially applicable to a wide range of animals and at different spatial scales.

510 **4.1 Performance comparison with state-of-the-art technologies used to** 511 **track flying insects**

512 Our new radar-based tracking system fills an important gap for future research on insect behavior. An
513 overview of a state of the art in flying insect tracking technology is given in Table 4. The mm-wave
514 solution proposed here allows to track an insect in 3D in a larger volume than optical technologies. At
515 these spatial scales, harmonic radars and radiotelemetry can only track in 2D (Kennedy et al., 2018;
516 Riley et al., 1996). In a previous work, we demonstrated that radar detection of an insect is possible
517 without a tag (Dore et al., 2020). Here we showed that appending a metallic tag (here a metallic cylinder)
518 to the same target increased the detection volume of the radar from 3.6m^3 to 5.3m^3 . We also showed
519 that the detection volume of the radar system can be considerably increased by combining several radar
520 units thereby opening the possibility to work at much larger spatial scales. Finally, although we have
521 illustrated the utility of our system for tracking bumblebees, in principle mm-wave radars can track
522 virtually any kind of small (flying or not) animals provided it can carry a passive metallic tag. Tracking
523 and posture monitoring of larger untagged animals using a similar approach was previously
524 demonstrated (Dore et al., 2021; Henry et al., 2023).

525
526

Table 4 – State of the art of insect tracking technology. If not explicitly mentioned in the paper, the feature value was estimated from other data in the paper. N/A means Not Applicable.

technology	dimension of the detection domain	detection range, surface or volume	spatial resolution (meter)	time resolution (frame per sec)	real-time image processing	goal	number of separate sensors	passive or active tag	tag weight (mg)	reference
HF RFID	1D	2.4mm	N/A	10	no	detection and id	1	passive	5	(Ohashi et al., 2010)
visible optics	1D	0.1m	N/A	60	no	detection	1	no tag	N/A	(Lihoreau et al., 2016a)
harmonic radar	2D	800m	2	3	no	tracking	1	passive	15	(Woodgate et al., 2017)
harmonic radar	2D	250m	7	20	no	tracking	1	passive	3	(Riley et al., 1996)
radio-telemetry	2D	800m	10	1	no	tracking	1	active	280	(Kennedy et al., 2018)
harmonic radar	2D	900m	10	1	no	tracking	1	passive	12	(Tahir and Brooker, 2011)
IR optics	2D	0.03m ²	0.001	2	yes	id	2	passive	2.4	(Crall et al., 2018)
IR optics	2D	0.05m ²	0.001	20	no	detection and id	2	no tag	N/A	(Manoukis and Collier, 2019)
visible optics	2D	0.03m ²	0.001	1	yes	id and tracking	1	passive	1.8	(Crall et al., 2015)
visible optics	2D	0.2m ²	0.001	60	no	id and tracking	1	no tag	N/A	(Ratnayake et al., 2021)
IR optics	2D	2.0m ²	0.1	100	yes	tracking	1	passive	13	(Walter et al., 2021)
UHF RFID	3D	1.0m ³	0.1	100	no	id and tracking	4	passive	3	(Särkkä et al., 2014)
visible optics	3D	0.5m ³	0.01	50	yes	id and tracking	3	no tag	N/A	(Lihoreau et al., 2016b)
visible optics	3D	27m ³	0.1	60	no	tracking	2	no tag	N/A	(Sun and Gaydecki, 2021)
stereo optics	3D	0.06m ³	0.1	47	no	tracking	1	no tag	N/A	(Chiron et al., 2013)
stereo optics	3D	N/A	N/A	160	N/A	detection	1	passive	20	(Vo-Doan et al., 2023)
depth IR optics	3D	0.8m ³	0.1	30	no	tracking	1	no tag	N/A	(Nasir et al., 2023)
visible optics	3D	0.01m ³	0.01	60	no	tracking and posture	3	no tag	N/A	(Ahmed and Faruque, 2022)
visible optics	3D	0.001m ³	0.001	20	no	tracking and posture	1	no tag	N/A	(Chen et al., 2021)
mm-wave radar	3D	3.6m ³	0.05	16.7	no	tracking	1	no tag	N/A	(Dore et al., 2020)
mm-wave radar imaging system	3D	5.3m³	0.05 *	16.7	no	tracking	1	passive	50	this work

527

* resolution in elevation is 6° and theoretical resolution is azimuth is 0.35°

528 4.2 About the detection rate

529 Our proposed detection algorithm enabled to extract target detections from images obtained from the
530 radar sensor. The overall target detection rate was found to be $\tau_d=15\%$ (5,601/38,428). This implies

531 that on average, from one in every seven radar scanning samples, a target detection could be derived.
532 Thus, the average target detection sampling rate was $T_d f_{scan} = 2.5 \text{ detections/s}$. In our experiments, the
533 bumblebees moved in the constrained volume at an average speed of 0.18m/s, thus an individual
534 moving at this average speed would be detected on average every 0.07m. In an unconstrained space,
535 a flying bee typically moves at an average speed of 4m/s which means that the detection spatial
536 resolution would be as high as 1.6m using the average target detection sampling rate obtained from our
537 experiments. However, this detection spatial resolution does not account for the varying posture of the
538 tagged individuals (and thus the tag orientation) relatively to the radar system during the radar scanning,
539 and the inevitable time-dependent electromagnetic clutter (see section 4.7).

540 **4.3 About the post-processing runtime**

541 The averaged processing time (computed over 15,000 samples) to generate one 3D image from raw
542 radar data applying the 2D-MUSIC algorithm was of about 13.2 seconds per 3D image. This implies that
543 the runtime to process a 30 seconds long radar recording was in average $500 \times 13.2s = 110 \text{ min}$. This
544 computation was performed on a HPC (High-Performance Computing) cluster of 16 CPUs (Intel E5-
545 2695 v4 2.1G) mounted in parallel using a total random-access memory (RAM) of 240GB. The resulting
546 3D-frame file has a size on disk on average of about 2.32MB. This implies that the size on disk of a 30
547 seconds long radar recording is on average $500 \times 2.32 \text{ MB} = 1.16 \text{ GB}$. Although real-time image processing
548 is not currently yet achievable with this tracking system, processing time and used disk space can be
549 reduced by decreasing the padding factor at the cost of less resolution in the final 3D images. Another
550 solution to reduce data size would be to crop radar images using spatial bounds enclosing a smaller
551 volume in which the target did not exit during the radar scanning. To justify the use of a 2D-MUSIC
552 algorithm to our application, we compared the detection accuracy performance resulting from the
553 analysis of images obtained by applying the implemented 2D-MUSIC algorithm raw data and that
554 resulting from the analysis of images obtained by applying the 2D-beamformer algorithm on the raw
555 data. To illustrate this comparison, we used the radar data collected from the radar measurements

556 performed to characterize the detection systems' detection volume in section 3.3. From the estimated
557 accuracy results shown in the Figure S3 in the Supplementary data section, we can infer that the
558 detection volume of the detection system using the 2D-beamformer algorithm (0.57m^3) is significantly
559 lower than that of the detection system using the 2D-MUSIC algorithm (5.25m^3). Thus, although the 2D-
560 beamformer algorithm is faster (0.9 seconds per 3D image) than the 2D-MUSIC algorithm (13.2 seconds
561 per 3D image), the 2D-MUSIC algorithm provides a better detection performance than the 2D-
562 beamformer algorithm. Other discrete source DOA estimation algorithms will be tested in future studies
563 to improve the efficiency of the detection process and reduce the computation time.

564 **4.4 About potential improvements on the flying insect tracking system**

565 The proposed tracking system presents encouraging results. Using metallic tags allowed to track a
566 tagged flying insect within bounds of a confinement box. This flight constraint allowed to collect
567 significantly more and longer 3D tracks than those obtained of untagged insects in previous work (Dore
568 et al., 2020) while requiring significantly less overall experiment time (i.e. only a few minutes). The
569 detection rate has been estimated to evaluate the quality of the obtained tracks. Information obtained
570 manually from ground-truth video recordings have allowed to confirm the 3D tracks obtained by the
571 radar 3D beam-scanning system.

572 While our 3D tracking radar system allows filling an existing technological gap, more improvements can
573 be made to meet the needs of biologists and ecologists for tracking flying individuals in 3D with high
574 resolution and in a large volume. Temporal resolution of the imaging system may be improved by
575 increasing measurement rate of the radar sensor. Detection rate and volume may also be improved by
576 increasing transmitted power or radar sensitivity. Although, per the radar link equation, doubling the
577 radar-to-target distance while keeping a fixed radar sensitivity requires to multiply the transmitted power
578 by $2^4=16$. In a more practical sense, as the radar sensor used in our experiments features a maximum
579 transmitted power of 10mW, the transmitted power that would be needed to detect a target at twice the

580 actual maximum distance of detection is 160mW. Managing signals carrying such power would require
581 more costly hardware. A much cheaper solution to increasing detection volume is to utilize a network of
582 multiple identical tracking FM-CW radar systems, as we have demonstrated in section 3.4.

583 As mentioned in the introduction, mounting imaging systems on UAVs to track insects on large spatial
584 scales has been investigated (Ju and Son, 2022; Kim et al., 2022; Lavrenko et al., 2021; Vo-Doan et
585 al., 2023). Embarking our radar imaging system on a UAV would require integrating a computer on the
586 UAV and reducing the mass of the overall imaging system. A more light-weight imaging system can be
587 achieved from choosing a lighter-weight rotating reflector (e.g. a metallic mesh grid) thus reducing the
588 motor torque needed to rotate the reflector at currently used angular speed. Thus a smaller less power-
589 consuming motor could be used instead of the one currently used to make the reflector rotate. The mm-
590 wave radar sensor itself is already light-weight compared to the mass of the mechanical beam-scanning
591 system. The effect of the air flow during flight on this beam-scanning system mounted on an UAV would
592 have to be studied.

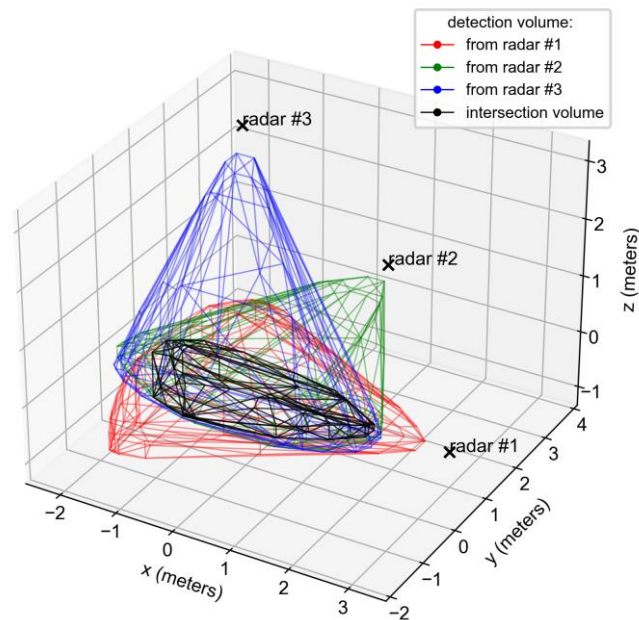
593 **4.5 About the detection and the tracking algorithms**

594 In the detection step, local maxima could have been simply detected by a gradient method or another
595 standard peak detection algorithm. However, the proposed segmentation method could be helpful (not
596 shown here) to define specific surfaces or volumes where targets should not be detected. As the future
597 aim of our study is to demonstrate the 3D tracking of flying insects using mm-wave radar as a proof-of-
598 concept, we assumed the presence of a single target and thus no ambiguous track assignments to
599 resolve (see section 2.1.4). However, future field studies require the possibility for the simultaneous
600 tracking of multiple flying insects moving and interacting in the scene, using a multi-target tracking
601 algorithm to solve the induced track assignment problem. In the era of extensive real-time video
602 surveillance, many *Multi-Object Tracking* (MOT) algorithms have been proposed to resolve multiple
603 tracks from a set of detections extracted from sensors in various contexts (Rakai et al., 2022; Smith et

604 al., 2019). Such an algorithm could be tested for the tracking of multiple bees flying in the same cage
605 using FM-CW radars.

606 **4.6 About deriving target speed from a Doppler analysis**

607 As mentioned in section 2.1.2, estimating the velocity directly from the radar data by applying a Doppler
608 analysis is not possible using the current 3D beamscanning system because the radar beam is steered
609 in elevation which would invalidate a Doppler analysis. As a potential solution, the use of three mm-
610 wave FM-CW radars working in range-Doppler mode would allow estimating the 3D location of a target
611 within the intersection volume of the three radar beams. Each radar would be oriented along one axis
612 of the Cartesian coordinates in order to estimate the 3D location of a target (see Figure 19). The 3D
613 location would be resolved from the range and velocity detection from each radar system. Using the
614 77GHz FM-CW radar commercialized by INRAS, the radar beam generated by this radar has a half-
615 power beamwidth in E-plane of 13.2° and a half-power beamwidth in H-plane of 51° . So far the volume
616 of the radar beam generated by a single radar sensor is of 6.7m^3 for a maximum range of 5meters.
617 Therefore, even assuming that the target would be detectable up until 5 meters, the intersection region
618 of the three radar beams in which a target would be detectable would have a volume of only 1.79m^3
619 which is smaller than the detection volume obtained by the 3D beamscanner system. Thus, the specific
620 radar sensor used in this study would not a good choice for multistatic range-Doppler 3D location
621 estimation. A radar sensor generating a larger radar beam would be a better fit for this purpose.



622

623 **Figure 19 - 3D representation of the radar beams generated by the three mm-wave radar sensors, each oriented**
 624 **towards one axis of the Cartesian coordinates (x, y, z).**

625 **4.7 About electromagnetic clutter**

626 The calibration step of the radar setup is necessary to mitigate the electromagnetic clutter generated by
 627 the bounds of the confinement volume. The so-called 3D-space reference image obtained from this
 628 calibration allows to mitigate static electromagnetic clutter. However, in the carried-out outdoors
 629 experiments, bounds of the confinement volume were slightly moving due to wind thus generating time-
 630 varying electromagnetic clutter. These variable undesirable radar echoes, which may generate false
 631 detections, cannot be mitigated by the above-described calibration technique. Setting spatial limits to
 632 select detections in the volume of interest allowed the mitigation of this time-varying electromagnetic
 633 clutter.

634 **4.8 About the passive tag attached to the insect**

635 Finally, the tag's mass (13% of an average bumblebee's weight) is large compared to the mass of
 636 harmonic radar tags (5%) but low compared to the mass of radio-telemetry active tags (75%). Future

637 improvements of tag design may come up with lighter tags. Importantly, the simple design of our passive
638 tags also opens the door for creating tags with different electromagnetic signatures for tracking multiple
639 individually identified insects flying simultaneously in the scanned scene, which is currently impossible
640 with harmonic radar systems. Multi-target tracking is readily possible with mm-wave radars as we have
641 demonstrated before (Dore et al., 2021, 2020). Moreover, in future work, we aim to study the impact of
642 the tag weight on the insect movement and flight.

643 **4.9 About the implementation of tracking in the case of a network of several** 644 **radar systems**

645 In section 3.4, we demonstrated the tracking of a tag for a network of three radar beamscanners. To
646 ensure the detection set obtained from each radar beamscanner had the same spatial reference, we
647 measured the location and orientation of each radar beamscanner relatively to an origin. However, there
648 may be a small timestamp delay between one radar beamscanner and another radar beamscanner.
649 Indeed, as the speed of each separate motor varies along time, (as mentioned in section 2.1.2), it is not
650 possible to synchronize the three mechanical beamscanners to point at the same time at the same
651 elevation angle. Therefore, the maximum timestamp difference between the timestamp recorded when
652 radar #1 points in a given elevation angle and that recorded when radar points at the same elevation
653 angle is of 60ms, i.e. the duration required for a 360° elevation beam scanning. Moreover, we assume
654 that tracks collected by the three radar systems are those of the target of interest. All the detections of
655 the three tracks (one per radar system) are then added in a single set that gives the total track of a
656 single target. The spatial interpolation (over time) of the total track is shown on figure 19b.

657 **5 Conclusions**

658 Our method based on a mm-wave radar imaging system for tracking passively tagged flying insects in
659 3D provides promising results. For verification purposes, tracks collected by the radar system have been
660 compared to those extracted from video recordings. From this comparison, correctly identified 3D tracks
661 of tagged flying individuals collected by the radar system add up to a total of 5.2 minutes. Potential

662 improvements on the radar system are proposed to increase its detection volume of tagged flying
663 individuals and track multiple identified individuals simultaneously, thereby providing new experimental
664 opportunities for research in insect behaviour and ecology.

665 **CRedit authorship contribution statement**

666 **Etienne Dedic:** Conceptualization (radar detection, experimental protocol), Investigation
667 (measurements, video annotations, signal processing), Data Curation, Writing – original draft, Writing –
668 review & editing. **Dominique Henry:** Conceptualization (radar detection), Writing – review & editing.
669 **Mathieu Lihoreau:** Resources (electrical and hive management), Writing – review & editing, Funding
670 acquisition. **Hervé Aubert:** Conceptualization (radar detection), Supervision, Writing – review & editing,
671 Funding acquisition.

672 **Declaration of competing interest**

673 The authors declare that they have no known competing financial interests or personal relationships
674 that could have appeared to influence the work reported in this paper.

675 **Data availability**

676 Data will be made available on request.

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