1 A non-invasive radar system for automated
2 behavioural tracking: application to sheep

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17 Abstract

18

19 Automated quantification of the behaviour of freely moving animals is increasingly
20 needed in ethology, ecology, genetics and evolution. State-of-the-art approaches often
21 require tags to identify animals, high computational power for data collection and
22 processing, and are sensitive to environmental conditions, which limits their large-scale
23 utilisation. Here we introduce a new automated tracking system based on millimetre-
24 wave radars for real time robust and high precision monitoring of untagged animals. To
25 validate our system, we tracked 64 sheep in a standard indoor behavioural test used for
26 genetic selection. First, we show that the proposed radar application is faster and more
27 accurate than conventional video and infrared tracking systems. Next, we illustrate how
28 new behavioural estimators can be derived from the radar data to assess personality
29 traits in sheep for behavioural phenotyping. Finally, we demonstrate that radars can be
30 used for movement tracking at larger spatial scales, in the field, by adjusting operating

31 frequency and radiated electromagnetic power. Millimetre-wave radars thus hold

32 considerable promises for high-throughput recording of the behaviour of animals with

33 various sizes and locomotor modes, in different types of environments.

34

35 Keywords: computational ethology, radar tracking, behavioural phenotyping, *Ovis aries*,

36 corridor test.

37

1. Introduction

39

40 Animal behaviour research increasingly requires automated recording and analyses of

41 movements (Branson et al., 2009). The emerging field of computational ethology

42 provides methods for high-throughput monitoring and statistical analyses of movements

43 that enable the quantitative characterisation of behaviour on large numbers of

44 individuals, the discovery of new behaviours, but also the objective comparison of

45 behavioural data across studies and species (Anderson and Perona, 2014; Brown and

46 de Bivort, 2018).

47 These quantitative approaches are particularly powerful to study inter-individual

48 behavioural variability or personalities in animal populations (Morand-Ferron et al.,

49 2015). In livestock, for instance, large-scale genetic selection programmes are based on

50 the measurements of several hundreds (if not thousands) of farm animals (O'Brien et al.

51 2014). Many behavioural tests have been developed to assess behavioural and

52 personality traits in farm animals (Canario et al. 2013), and some applications have

53 been developed in breeding programmes for instance to discard the more aggressive

54 individuals for beef cattle production (Phocas et al. 2006). Behavioural measures are

55 frequently obtained from direct observations by the experimenters or farmers (e.g.,

56 Boissy et al., 2005), limiting use of behavioural criteria for breeding programmes.

57 Indeed, the absence of automated measurements make data collection cumbersome,

58 time-consuming and prone to biases, which currently limits the ability to quantify

59 behavioural traits at the experimental or commercial farm level.

60 Tracking methods involving on-board devices, such as Global Positioning

61 Systems (GPS) (Tomkiewicz et al., 2010), radio telemetry (Cadahia et al., 2010), radio

62　frequency identification (RFID) (Voulodimos et al., 2010) or harmonic radar (Riley et al.,

63　1996), are hardly suitable for detailed high throughput behavioural phenotyping due to

64　the limited accuracy and duration of measurements. Best available methods therefore

65　involve image-based analyses (Pérez-Escudero et al., 2014; Romero-Ferrero et al.,

66　2019). However, these techniques often require large computational resources to

67　acquire and process images (Garcia et al 2019) and are sensitive to light variation (Dell

68　et al., 2014).

69　　　　Recently, Frequency-Modulated Continuous-Wave (FMCW) radars operating in

70　the millimetre-wave frequency band have been proposed for automated tracking of

71　animal behaviour (sow: Dore et al., 2020b, bees: 2020a; sheep: Henry et al., 2018). In

72　this approach, it is possible to record the 1D movements (distance to radar) of individual

73　sheep in an arena test (Henry et al., 2018). Tracking with FMCW radars has the great

74　advantage of being non-invasive (does not require a tag), insensitive to light intensity

75　variations, and fast (as it does not require large memory resource). FMCW radars

76　therefore provide considerable advantages for the development of automated high-

77　throughput analyses in regard to more conventional approaches (e.g. video and infrared

78　tracking systems).

79　　　　Here we developed a millimetre-wave FMCW radar system for automated

80　tracking and analyses of the 2D trajectories of freely moving animals. We illustrated our

81　approach by analysing the behaviour of 64 sheep in an "arena test" commonly used to

82　estimate the sociability of individual sheep in genetic selection (Boissy et al., 2005;

83　Hazard et al., 2014). First, we compared the speed and accuracy of radar tracking with

84　more conventional video and infrared tracking systems. We then derived new

85　behavioural estimators computed from the radar data, that could be used for large-scale

86　behavioural phenotyping. Finally, we tested the radar system for long-distance tracking,

87　in the field, by adjusting radar emission frequency and radiated electromagnetic power.

88

89　## 2. Materials and methods

90

91　**Sheep**

92

93   We ran the experiments in July 2019 at the experimental farm La Fage of the French
94   National Research Institute for Agriculture, Food, and Environment (INRAE), France
95   (43.918304, 3.094309). We tested 64 lambs (32 males, 32 females) *Ovis aries* with
96   known weight (range: 12kg – 31.3kg) and age (range: 59 days – 88 days). Ewes and
97   their lambs were reared outdoor on rangelands. After weaning, lambs were reared
98   together outside and tested for behaviour 10 days later. This delay allowed the
99   development of social preferences for conspecifics instead of preference for mother. All
100   the lambs were previously tested in a "corridor test" to estimate their docility towards a
101   human. Briefly the test pen consisted of a closed, wide rectangular circuit (4.5 x 7.5 m)
102   with opaque walls (Boissy et al., 2005). A non-familiar human entered the testing pen
103   and moves at constant speed through the corridor until two complete tours had been
104   achieved. Every 5 s (i.e. the corridor was divided into 6 virtual zones and 1 zone was
105   crossed every 5 s by the human) the zones in which the human and the animal were
106   located were recorded and the mean distance separating the human and the lamb was
107   calculated. The walking human also recorded with a stopwatch the total duration when
108   the human saw the head of the lamb to discriminate between fleeing and following
109   lambs. The reactivity criteria towards an approaching human was constructed by
110   combining both measurements (for more details see Hazard et al., 2016). The higher
111   was the resulting variable (i.e. docility variable), the more docile was the animal.

112

113   **Arena test**

114

115   We tested all the sheep in the arena test, a standard protocol for assessing the
116   sociability of sheep through measures of inter-individual variability in social motivation in
117   the absence or presence of a shepherd (Boissy et al., 2005; Hazard et al., 2014). Briefly,
118   a sheep (focal sheep) was introduced in the pen (2mx7m) with artificial lights (Fig. 1A;
119   for more details see Ligout et al. 2011). Three other sheep from the same cohort (social
120   stimuli) were placed behind a grid barrier, on the opposite side of the corridor entrance.
121   The test involved three phases (Fig. 1B). In phase 1, the focal sheep could explore the
122   corridor for 15s and see its conspecifics through a grid barrier. In phase 2, visual contact
123   between the focal sheep and the social stimuli was disrupted using an opaque panel

124   pulled down from the outside of the pen. This phase was used to assess the sociability

125   of the sheep towards its conspecifics and lasted 60s. In phase 3, visual contact between

126   the focal sheep and its conspecifics was re-established and a man was standing still in

127   front of grid barrier for 60s. This phase was used to assess the sociability of the focal

128   sheep towards conspecifics in presence of a motionless human.

129

130   **Data collection**

131

132   We measured the displacement of the focal sheep in phases 2 and 3 of the arena test

133   (phase 1 is the initiation phase) using three automated tracking systems: infrared

134   sensors, a video camera, and a millimetre-wave FMCW radar. During the measures, an

135   experimenter also recorded the number of high-pitched bleats by the focal sheep, a

136   proxy of the sociability (i.e. sociability variable) of the sheep (Boissy et al., 2005).

137

138   <u>Tracking with infrared cells</u>

139

140   Infrared cells were previously used to quantify sheep behaviour in the arena test. We

141   placed two infrared sensors every meter along the arena length (Fig. 1A). We used two

142   infrared sensors to determine the direction of the moving sheep. The focal sheep was

143   recorded each time it passed through one of these sensors. Sheep movements were

144   thus tracked in 1D (longitudinal movements in the corridor) and data resolution was 1m.

145

146   <u>Video tracking</u>

147

148   We placed a video camera on one end of the arena (opposite to entrance side, Fig. 1B).

149   The camera was elevated 2m above ground in order to film the entire arena. Sheep

150   movements were tracked in 2D. For image processing, we applied a detection algorithm

151   using the state-of-the-art image object detector tiny-YOLO (You Only Look Once)

152   network, which is a version of the YOLO model adapted for faster processing allowing

153   244 images of 0.17 mega pixels (416 x 416 pixels) per second (on a TITAN X graphics

154 card) (Redmon et al., 2016). This neural network was pre-trained on the PASCAL Visual

155 Object Classes Challenge dataset (Everingham et al., 2012).

156

157 <u>Radar tracking</u>

158

159 We placed a millimetre-wave FMCW radar (Fig. 1C, see technical characteristics in

160 Table 1) at one end of the arena (entrance side, Fig. 1B). The radar was setup outside

161 of the test pen behind a Styrofoam wall transparent to millimetre-wave (Dietlein et al.,

162 2008). The transmitting antenna array radiated a repetition over time of a so-called chirp

163 (i.e. a saw-tooth frequency-modulated signal (Balanis, 2011)). The chirp was

164 backscattered by the targeted focal sheep, but also by the surrounding scene which

165 provides undesirable radar echoes called the electromagnetic clutter. The total

166 backscattered signal was then collected by the receiving antenna array and processed

167 to mitigate the clutter and to derive the sheep 2D trajectory from radar data. In the

168 millimetre-wave frequency range, the detectability of the sheep depends mainly on the

169 bandwidth of the frequency modulation, the beamwidth of the radar antennas, and the

170 radiated electromagnetic power (Balanis, 2011)).

171

172 **Radar signal processing**

173

174 Processing of radar data included two main steps. First, we extracted the position of the

175 animal. Next, we computed behavioural parameters to characterize the movement of the

176 animal.

177

178   Extraction of sheep positions

179

180   We extracted the distance of the focal sheep to the radar and its direction in the
181   horizontal plane of the scene. To mitigate the electromagnetic clutter, we estimated the
182   mean value (*mean*) and standard deviation (*std*) of the signal provided by the radar in
183   absence of the sheep and derived the signal *Detection*(r, θ) from the signal S$_{radar}(r, \theta)$
184   delivered in presence of the animal, as follows:

$$Detection(t, r, \theta) = \frac{S_{radar}(t, r, \theta) - mean(r, \theta)}{std(r, \theta)}$$

185   Where r is the distance to the sheep, *mean* is the time-averaged signal radar coming
186   from the range r and angular position θ, *std* is the time-standard deviation of the radar
187   signal. Fig. 1D shows an example of position estimations of a sheep over time after
188   removing the clutter.

189

190   Extraction of new behavioural parameters

191

192   From the 2D trajectory data, we extracted new behavioural parameters to characterize
193   sheep movements using three approaches.

194

195   *Computation of behavioural classes*

196

197   We statistically identified broad classes of behaviour using automated classification.
198   First, we extracted movement parameters (speed, sinuosity and speed of displacement)
199   from the trajectories. Then, to differentiate the movement modifying the distance of the
200   sheep from the social stimuli (i.e. the three conspecifics) and a lateral movement, the
201   speed vector was split in two dimensions: along the two lateral walls of the corridor and
202   across the two longitudinal walls. These characteristics were estimated on time windows
203   of 1s for each sheep and for each experimental phase. Finally, to derive behavioural
204   classes, we performed an extraction from a Gaussian mixture model using the extracted
205   data for each lamb (Reynolds and Rose, n.d.). The number of classes (i.e. the number

206   of Gaussians to be used) was determined by comparing models using 1 to 15 classes.

207   We selected the model with the lowest Akaike score which represents the model with

208   the features best explaining the parameter under consideration (Burnham and

209   Anderson, 2002).

210

211   *Computation of behavioural transitions*

212

213   We determined behavioural changes over time using Ricker wavelet processing (Ryan,

214   1994; see examples Fig. 3). Wavelet processing consists in filtering the sheep position

215   signal using a wavelet as a filter (Poirier et al., 2009). This type of filtering is applied to

216   several time scales, thus allowing the detection of a behaviour regardless of how long

217   this behaviour lasts. Our aim was to determine the precise moments when the focal

218   sheep changed its moving behaviour, which was estimated using the spectrum

219   described by each wavelet. We observed that the number of local maxima in the wavelet

220   transform coefficients is sensitive to the number of behaviour changes (see example in

221   Fig. S1B).

222

223   *Computation of space coverage*

224

225   We investigated the space occupied across time by the focal sheep using heatmaps

226   (see examples Fig. 4). We partitioned the arena into 80 zones of 44x40cm each (i.e. 16

227   partitions along the arena length and 5 partitions along the arena width). We chose this

228   zone dimension because it corresponded to the width of a small lamb (Idris et al., 2011).

229   We counted the number of zones the focal sheep remained in for more than 200ms. We

230   considered that a lamb stayed in a given zone for less than 200ms either because it was

231   positioned at the edge of this zone or because the estimation of position by the radar

232   was inaccurate (this situation occurred for less than 10% of detections).

233

234   **Outdoor radar tracking**

235

236   We ran outdoor experiments in order to demonstrate the applicability of our radar
237   system for long-range tracking of sheep (Fig. 4). These measurements where done in
238   an open space with no obstacles (60m x 15m). A man moved in order to induce animal
239   movements. We tested one female sheep (2 years, 60 Kg). To enhance detection range
240   to 40 m, we used a FMCW radar with a lower operating frequency (24GHz; (Simon et
241   al., 2014)). At constant transmitted power, lower frequencies enables to reduce the free-
242   space attenuation of the radiated electromagnetic power (Balanis, 2011). We used the
243   same signal processing as with the 77GHz radar.

244

245   **Statistical analyses**

246

247   We ran all analyses using the programming environment R(R Core Team, 2014). Raw
248   trajectory data extracted from radar and video measures are available in Dataset S1.

249

250   Comparison of the performances of the different tracking systems

251

252   We tested the ability of radar and video tracking systems to capture the same
253   information as the infrared cells from the computation of two parameters: (1) a crossing
254   rate and (2) a proximity score (respectively LOCOM and PROX in Hazard et al. 2014).
255   The crossing rate is the number of times the animal moved between virtual zones
256   defined by the infrared cells (1x2m) without distinguishing between the zones nor the
257   direction of movement. This rate thus provides information on the displacement activity
258   of animals seeking contact with their conspecifics. The proximity score is the total
259   duration the focal sheep remained in each zone weighted as the animal moves closer to
260   its conspecifics. The weight depends on the distance between the sheep and the
261   conspecifics:

$$w_i = \frac{1}{i}$$

262   with w_i the weight of the zone considered, i the index of the zone delimited by the
263   infrared sensors. $i = 1$ corresponds to the zone close to the conspecifics, and $i = 7$
264   corresponds to the zone close to the corridor entrance. Thus, an animal with a high
265   proximity score spent more time close to its conspecifics. We calculated these two

266 parameters from data collected from infrared cells, video and radar tracking systems

267 and compared them using Pearson's correlation tests (using 'stats' R package).

268 We compared the accuracy of radar and video data systems by running a general

269 linear mixed model (GLMM using glmer function in 'lme4' R package (Bates et al.,

270 2014)) testing the effect of the tracking method on the proportion of false detections,

271 with sheep identity as random factor. We estimated the correlation between the number

272 of false detections with the two methods using the Pearson's correlation test.

273

274 Analyses of new movement features

275

276 We tested the influence of the sheep characteristics on behavioural classes using

277 generalised models (GLMMs). Models (binomial family) tested the effects of phase,

278 docility, weight, age, sociability, sex, and dual interactions of each variable with test

279 phase, on the proportion of time spent in fast movements (behavioural class 2).

280 Interactions between more than two variables were excluded because of the high

281 number of variables relative to sample size. Sheep identity was included as a random

282 factor. We ran a model selection by using all features combinations (age, weight,

283 docility, sociability, sex and the phase when the radar measurement was done). We kept

284 the model with the highest Akaike score. We used a similar procedure to test the

285 influence of the sheep characteristics of the lambs on continuous wavelet transforms

286 (Gaussian models) and heatmaps (Poisson models). For the continuous wavelet

287 transform, we performed two different wavelet transforms on the lateral and on the

288 longitudinal position of the sheep. For heatmaps, we tested different grid resolutions

289 characterised by zone sizes: a low resolution grid with 21 zones (3 x 7) and a high

290 resolution grid with 45 zones (5 x 15).

291

292 Classification of behavioural types

293

294 To classify sheep from on our new behavioural estimators, we ran a principal

295 component analysis (PCA) based on the eight behavioural measures extracted from the

296 radar data in phase 2 and phase 3: proportion of fast movements (class 1) out of all

297 movements (class 1 + class 2), longitudinal movements (wavelets Y), latitudinal
298 movements (wavelets X), space coverage (heatmaps).

299

300 **3. Results**

301

302 **Radar tracking is more faster and more accurate than video tracking**

303

304 To validate the radar tracking system, we compared the data obtained from the infrared
305 cells, video and radar. We analysed data from 58 (29 males, 29 females) out of the 64
306 sheep initially tested, because some recordings failed during measurements due to
307 human errors or miss detection by infrared cells.

308   Both data collected by radar and video enabled to capture information given by
309 infrared cells with high fidelity. Proximity scores and crossing rates obtained from
310 infrared cells were positively correlated with data obtained from radar (Pearson
311 correlation; proximity: $r = 0.77$, $p < 0.001$; crossing rate: $r = 0.87$, $p < 0.001$) and video
312 (Pearson correlation test; proximity: $r = 0.91$, $p < 0.001$; crossing rate: $r = 0.34$, $p =$
313 <0.001). Imperfect correlation between proximity scores and crossing rates obtained
314 from different tracking methods are caused by the different reference points used for
315 tracking: infrared cells detect the full body of the sheep, whereas image analysis detects
316 the centre of mass of the sheep, and the radar detects body parts of the sheep that are
317 closest to it.

318   The comparison between the radar and the video data showed both tracking
319 systems involved low levels of false detections (i.e. when the distance between the body
320 centre of the sheep and its estimated position is greater than one sheep body length).
321 However, radar tracking generated ca. three times less false detections than video
322 tracking (Binomial GLMM, $z = -3.595$, $p < 0.001$; Table 2). False detection with the two
323 methods had different origins. False video detections resulted from insufficient colour
324 contrast between the lamb and the background (e.g. when the lamb was close to the
325 wall of the corridor), whereas false radar detections resulted from the low angular
326 resolution of the radar and potential multiple reflections of the transmitted
327 electromagnetic signal by obstacles in the scene (such as walls, ground, human). Radar

328   and video tracking systems are therefore complementary. The combination of the two

329   systems gave the exact position of the sheep in 97.83% of the measures.

330   Radar tracking had additional advantages over video tracking in terms of data

331   processing (Table 2). The radar produced two times more measures per second. Radar

332   processing was also much faster and therefore it may be used for real time data

333   analyses. Radar measures were of similar size as video measures (ROM), but required

334   ca. 7 times less memory (RAM) to process. Finally, radar processing did not require a

335   learning phase with important data collection and a time-consuming training phase that

336   can last several hours just for the adaptation of the model, or several days if the network

337   is not trained beforehand.

338

339   **New behavioural indicators from radar data**

340

341   The following analyses were made on the 64 sheep tested (32 males, 32 females). The

342   obtained 2D trajectory data offered the opportunity for high resolution analyses of sheep

343   movements.

344

345   Behavioural classes: detection of slow and fast movements

346

347   We applied a Gaussian Mixture Model (GMM) procedure to statistically identify

348   behavioural classes from the 2D trajectory data. We found four behavioural classes (Fig.

349   2A). Class 1 (51.3% of measures) was characterized by null or slow movements ("slow

350   movements"). Class 2 (35.48% of measures) was characterized by fast movements with

351   low sinuosity ("fast movement"). Class 3 (10.2% of measures) was characterized by fast

352   movements with high sinuosity ("fast tortuous"). Class 4 (3.01% of measures) was

353   characterized by slow movements with high sinuosity ("slow tortuous"). Each of the two

354   behavioural classes with strong sinuosity (classes 3 and 4) represented less than 10%

355   of all data. We thus focused our analyses on slow and fast movements (classes 1 and

356   2).

357   We tested the effects of the individual characteristics of sheep on time spent in

358   each behavioural class using GLMMs. Results of the best model (i.e. highest Akaike

359   score) are summarized in Table 3 (see model selection in Table S1). Male, old, large

360   and highly docile sheep spent significantly more time in slow movement during phase 3

361   than during phase 2 (Fig. 2C). Highly sociable sheep also spent more time in slow

362   movements during phase 3 than during phase 2 (Fig. 2D).

363

364   <u>Wavelet analyses: detection of erratic behavioural transitions</u>

365

366   We quantified behavioural changes during time (variation in speed, direction, or both)

367   using continuous wavelet analyses. We tested the effects of the individual

368   characteristics of sheep on the frequency of behavioural changes using GLMMs and

369   model selection (Tables S2 and S3). When considering longitudinal movements along

370   the corridor length (Table 4A), we found that males made more behavioural transitions

371   in phase 3 than in phase 2. Highly sociable sheep made more behavioural transitions in

372   phase 3 than in phase 2 (Fig. 3A). When considering latitudinal movements along the

373   corridor width (Table 4B), we found that highly docile sheep made more behavioural

374   transitions in phase 3 than in phase 2 (Fig. 3B). Thus overall, wavelet analyses of

375   longitudinal movements can be used as a proxy of sociability, and analyses of latitudinal

376   movements give information about docility.

377

378   <u>Heatmap analyses: Detection of occupied space</u>

379

380   We quantified spatial coverage by individual sheep (number of zones occupied in the

381   corridor) using heatmaps. We tested the effects of the individual characteristics on the

382   number of zones in which the sheep spent more than 200ms using GLMMs and model

383   selection (Tables S4 and S5). When considering a grid with low spatial resolution, i.e.

384   similar zone dimensions as with infrared cells (i.e., dimension: 0.6 x 1m; example Fig.

385   4A), we found that sheep used 2.37 times less space in phase 3 than in phase 2 (Table

386   5A). Larger individuals used more space than smaller ones (Table 5A). Increasing the

387   spatial resolution of the grid, i.e. similar zone dimension as a lamb body size (i.e.

388   dimension: 0.44 x 0.40 m; example Fig 4A), revealed that highly docile sheep used more

389   space in phase 3 than in phase 2 (Table 5B). Young and highly social individuals used

390   more space than old and poorly social individuals in both phases. Body size effect,
391   however, was not significant anymore. Therefore, heatmap analyses are sensitive to
392   grid size resolution. Decreasing grid size increased behavioural resolution.

393

394   **Sheep behavioural phenotype**

395

396   We explored whether the new behavioural measures extracted from the radar data
397   could capture information from behavioural traits measured manually by the
398   experimenter in the corridor test. We focused on docility and sociability.

399   We ran a PCA based on the eight behavioural measures extracted from the radar
400   data in phase 2 and phase 3: proportion of fast movements (class 1) out of all
401   movements (class 1 + class 2), longitudinal movements (wavelets Y), latitudinal
402   movements (wavelets X), space coverage (heatmaps). We retained two PCs using the
403   Kaiser-Guttman criterion (Kaiser, 1991). PC1 explained 36% of the variance and PC2
404   explained 22% of the variance. PC1 was positively associated with all behavioural
405   variables (Fig. 5A). Sheep with high PC1 values moved more often faster, made more
406   behavioural transitions, and used more zones than sheep with low PC1 values. We
407   therefore interpreted PC1 as a "movement speed" variable. PC2 was positively
408   associated with the four behavioural variables of phase 3 and negatively associated with
409   the four behavioural variables of phase 2 (Fig. 5A). Sheep with high PC2 values showed
410   a more important increase of time spent moving fast, of the frequency of behavioural
411   transitions, and numbers of zones occupied from phase 2 to phase 3 than sheep with
412   low PC2 levels. We interpreted PC2 as a variable of "movement increase between
413   phases".

414   Sociability was significantly explained by PC1 (LM, PC1: estimate = 0.027, t =
415   2.552, p = 0.014; PC2: estimate = -0.104, t = -0.764, p = 0.448; Fig. 5B). Docility was
416   significantly explained by PC2 (LM, PC1: estimate = -0.081, t = -0.943, p = 0.350; PC2:
417   estimate = 0.283, t = 2.547, p = 0.014; Fig. 5C). Therefore, the automatically extracted
418   radar data can capture inter-individual variability in sociability and docility traits usually
419   measured by experimenters.

420

421 **Outdoor radar tracking**

422

423 To demonstrate that our tracking system can be used in various experimental contexts,

424 we tracked sheep in an outside corridor at a larger spatial scale (10 x 60m; Fig. 6A). We

425 monitored the 2D trajectory of one sheep over a maximum distance of 45m (Fig. 6B).

426 The presence of the man to induce sheep movement did not impair tracking (Fig. 6C).

427

428 # Discussion

429

430 Research in behaviour and ecology increasingly requires automated monitoring and

431 annotation of animal movements for comparative quantitative analyses (Anderson and

432 Perona, 2014; Brown and de Bivort, 2018). Here we introduced a radar tracking system

433 suitable to study the 2D movements of sheep within a range of 45 m. The system is non-

434 sensitive to light variations, compatible with real time data analyses, transportable, fast

435 processing and adaptable to various species and experimental contexts. Moreover, it

436 does not require to use tags or transponders for tracking the animals. It is therefore

437 suitable for the collection of large sets of behavioural data in an automated way required

438 in many areas of biological and ecological research.

439 FMCW radars were recently used to track sheep and pigs in 1D (Dore et al.,

440 2020b; Henry et al., 2018) and bees in 3D (Dore et al., in press). Here, for the first time,

441 we demonstrate the applicability of this approach to monitor 2D trajectories of untagged

442 walking animals within a range of 45 meters with high spatial resolution. Radar

443 acquisition system has several advantages over more conventional methods, and in

444 particular video tracking, as it collects more data per seconds, requires less RAM, less

445 processing time (e.g. does not require to train neural networks) and generates less false

446 detection rates. It can therefore be applied for real-time detection of animal position.

447 Importantly, the radar is not dependent on brightness and can be used for outside

448 tracking over long distances by adjusting operating frequencies. It also enables the

449 tracking of individualised animals without tags, based on the size and shape of the radar

450 echoes of the different targets. Others methods can be used to estimate the sheep

451 position. The main two methods are video detection (Bonneau et al., 2020), which can

452   detect sheep in 2D up to 25m but with a precision of about 2m, and GPS detection
453   (Gwyn et al., 1995), but this requires to animals.

454   Our application of radar-based tracking to behavioural phenotyping of sheep
455   shows that the radar analysis is consistent with current manual or semi-automated
456   analyses. we found that sheep tend to have a greater displacement in phase 2 than in
457   phase 3 of the corridor test. This is consistent with previous work showing that sheep
458   are more active when socially isolated, presumably as the result of them searching for
459   social contact with conspecifics. These docile animals tend to move less when they are
460   in contact with men. Importantly, the high resolution 2D trajectories obtained from the
461   radar enabled to identify new behavioural estimators that could greatly benefit the fast
462   and automated identification of behavioural phenotypes. These different estimators are
463   not dependent on the radar tracking system per se, but requires to detect the position of
464   the sheep with sufficient time resolution. For example, our application of unsupervised
465   behavioural annotation to identify statistically significant behaviours by sheep in the
466   corridor test showed that sheep exhibit less fast movements in phase 3 than in phase 2.
467   Our utilisation of wavelet analyses revealed the occurrence of erratic displacements.
468   The more the sheep was sociable the more it made erratic longitudinal movements. The
469   more the sheep was docile, the more it made erratic latitudinal movements. We also
470   analysed space occupation by sheep, showing that individuals exploit narrower areas in
471   phase 3 than in phase 2. All these results are consistent with previous observations
472   using manual or semi-automated recording methods. Most importantly, the combination
473   of these new automatically computed estimators appears to be correlated with
474   behavioural traits of interest that were until now measured manually by an experimenter
475   during the corridor test or in complementary tests (e.g. carousel test). Therefore, in
476   principle, our automated tracking and analysis system can be used for automated
477   classification of animal behavioural profiles, which is a major issue for mass phenotyping
478   in animal selection (Beausoleil et al., 2012). Note however that our pioneering study is
479   based on relatively low sample sizes (64 individuals) and further measurements are
480   needed to verify the biological trends observed on a much larger number of sheep.

481   Beyond genetic selection of farm animals, our system can be tuned to suit a large
482   diversity of animal sizes and experimental contexts. Range and resolution of detection

483 can be improved using different radars. For instance, we had to placed the radar at 1
484 meter from the corridor in order to track the entire corridor area. But with other antennas
485 and a radar with larger field of view could have been placed at the edge of the corridor.
486 Moreover, the detection was limited to a few meters but it is possible to detect a sheep
487 at tens of meters using a radar operating at a lower frequency (24GHz) and/or
488 transmitting higher electromagnetic power. It is also possible to improve radar detection
489 by using more antennas. Indeed, by multiplying the number of antennas, we multiply the
490 number of signal estimations and then the noise from the radar can be decreased. In the
491 future, the same radar technology could be used to track individuals in groups over
492 longer distances in open fields, for instance to explore the mechanisms underpinning
493 social network structures and collective behaviour (Ginelli et al., 2015; King et al., 2012).
494 Furthermore, it is possible to improve the processing of the radar signal for tracking
495 large number of sheep simultaneously by using deep radar processing but this would
496 require the use of a large amount of annotated data to train the neural networks (Huang
497 et al., 2018). Individual tracking within groups could be improved with non-invasive
498 passive tags that depolarize radar signal in specific directions (Lui and Shuley, 2006).

499 To conclude we demonstrate the feasibility of tracking a sheep in a restricted
500 area using a FMCW radar. This detection is possible even if each wall of the corridor
501 backscatters the transmitted electromagnetic signal. This radar can also be
502 advantageously used to extract features that are relied to the movement of the sheep
503 and can estimate if it is erratic, fast and the space occupied in the corridor. In contrast to
504 other short-range methods, this 2D detection method does not require pre-annotated
505 data and can be applied in real time. This flexibility holds considerable premises for
506 tracking the behaviour of animals of various sizes and environments in a wide range of
507 contexts and research fields.

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623   **Tables**

624

625   **Table 1**: Technical characteristics of the FMCW radar used for indoor tracking (Haderer

626   et al., 2008) and outdoor tracking (Simon et al., 2014).

627

Name	Indoor tracking	Outdoor tracking	Note
Operating frequency	77GHz	24GHz	This frequency is also called the *carrier frequency* of the frequency-modulated signal transmitted by the radar
Modulation Bandwidth	3GHz	800MHz	Frequency interval, centred at the operating frequency, used for the saw-tooth frequency modulation of the transmitted signal
Resolution	5cm	18.75cm	Resolution $= \frac{c}{2B}$, with c the celerity and B the modulation bandwidth
Ramp time	256 µsec	1ms	Up-ramp duration of the saw-tooth frequency-modulated signal (or chirp duration)
Repetition time	50ms	30ms	Period of the transmitted frequency-modulated signal (or chirp repetition interval)
Number of linear arrays in the transmitting array antenna	4	1	One linear array composed of 8x2 rectangular patches radiating elements
Number of linear arrays in the receiving array antenna	8	2	Eight linear arrays composed of 8 rectangular patches radiating elements
Main lobe beamwidth of the transmitting array antenna in the horizontal plane	50°	58°	Angular range (or field of view) of the radar illumination in the horizontal plane
Transmitted power	100mW	100mW	Power delivered at the input terminals of the transmitting array

			antenna (the radiated power is defined as the product of the transmitted power by the efficiency of the antenna)

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633 **Table 2**: Comparison of data processing characteristics with radar and video tracking

634 systems.

635

Tracking method	Radar	Video
Number of measures per second	50	25
Read Only Memory (ROM) for all measures of a sheep	151Mo	62Mo
Random Access Memory (RAM) per measure	524Kb	3.7Mb
Processing time per measure	<20ms	250ms
Total false detection rate	6%	16%

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638 **Table 3:** Analyses of behavioural classes. Results of the best GLMM (binomial family,
639 after model selection – see Table S1). The model tested the effects of phase, docility,
640 weight, sex, age, sociability, and dual interaction of each variable with phase, on the
641 proportion of time spent in fast movements (behavioural class 2). Sheep identity was
642 included as a random factor. Significant effects (p<0.05) are shown in bold.

643

Variable	Estimate	z-value	P-value
Phase	**-1.272453**	**-102.321**	**< 0.001**
Docility	**-0.134811**	**-2.725**	**0.006**
Weight	0.042312	0.753	0.451
Sex	-0.018224	-0.165	0.869
Age	-0.095193	-1.673	0.094
Sociability	**0.137659**	**3.596**	**< 0.001**
Phase x docility	**0.156352**	**19.868**	**< 0.001**
Phase x weight	**0.046431**	**5.223**	**< 0.001**
Phase x sex	**0.068090**	**3.882**	**< 0.001**
Phase x age	**0.078200**	**8.537**	**< 0.001**
Phase x sociability	**-0.127900**	**-20.900**	**< 0.001**

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647 **Table 4:** Wavelet analyses. Results of the best GLMM (Poisson family, after model
648 selection – see details in Tables S2 and S3). The model tested the effects of phase,
649 docility, weight, sex, age, sociability, and binary interactions of each variable with phase,
650 on the number of wavelets. Lamb identity was included as a random factor. Significant
651 effects (p<0.05) are shown in bold. Wavelet Y: longitudinal movements. Wavelet X:
652 latitudinal movements.

653

	Variable	Estimate	t-value	P-value
Wavelet	**Phase**	**513.352**	**54.603**	**<0.001**

Y	Sex	-11.392	-0.835	0.405
	Weight	2,417	0.349	0.727
	Age	-3,875	0,552	0.582
	Docility	-3.342	-0,548	0.585
	Sociability	**17.371**	**3.679**	**<0.001**
	Phase x sex	**38.656**	**2.103**	**0.0403**
	Phase x weight	1.941	0.208	0.836
	Phase x age	-2.426	-0.257	0.798
	Phase x docility	1.253	0.152	0.879
Wavelet X	**Phase**	**-67.0684**	**-5.68335**	**< 0.001**
	Sex	-2.70137	-0.21731	0.828
	Weight	-1.28441	-0.203557	0.839
	Age	-0.193189	-0.0302208	0.976
	Docility	-9.23551	-1.66137	0.100
	Sociability	0.669471	0.155654	0.877
	Phase x sex	27.8832	1.64681	0.106
	Phase x weight	-5.40654	-0.629084	0.532
	Phase x age	-1.34492	-0.154463	0.878
	Phase x docility	**17.9056**	**2.36483**	**0.022**
	Phase x sociability	7.0736	1.207	0.233

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656 **Table 5:** Heatmap analyses. Results of the best GLMM (Poisson family, after model
657 selection – see details in Tables S4 and S5). The model tested the effects of phase,
658 docility, weight, sex, age, sociability, and dual interactions of each variable with phase,
659 on the number of areas where the lamb spent more than 1s. Sheep identity was
660 included as a random factor. Significant effects (p<0.05) are shown in bold. A. Low
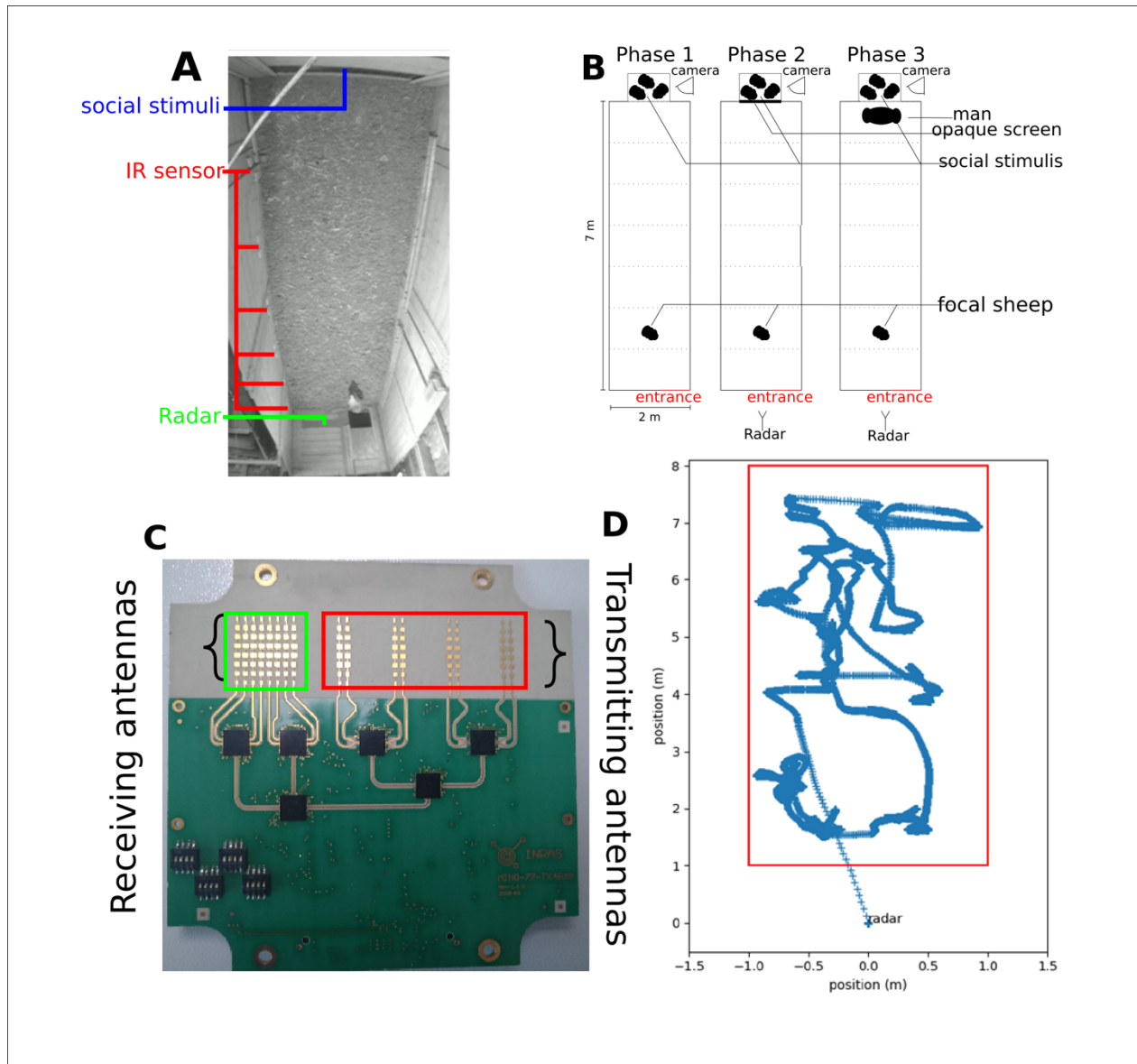661 spatial resolution. B. High spatial resolution.

662

	Variable	Estimate	t-value	P-value
A	**Phase**	**-0.597701**	**-9.20941**	**< 0.001**
	Weight	**0.0615106**	**1.99628**	**0.046**
	Sociability	0.0365622	1.63703	0.102
B	Sex	0.0188161	0.299427	0.765
	Age	**-0.0653912**	**-2.04381**	**0.041**
	Phase	**-0.765708**	**-14.4685**	**< 0.001**
	Docility	**-0.0837715**	**-2.665**	**0.008**
	Sociability	**0.0480015**	**2.19218**	**0.029**
	Weight	0.0407016	1.27774	0.201
	Phase x docility	**0.0978634**	**2.15262**	**0.031**

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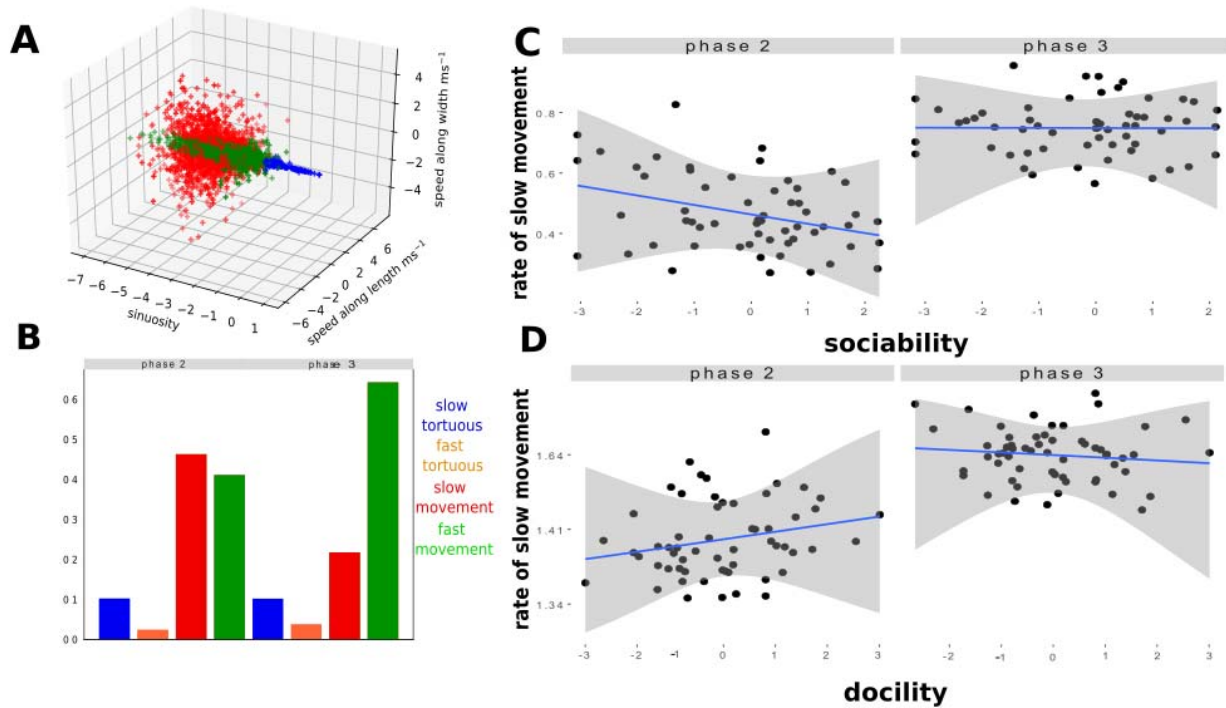
665 **Figures**
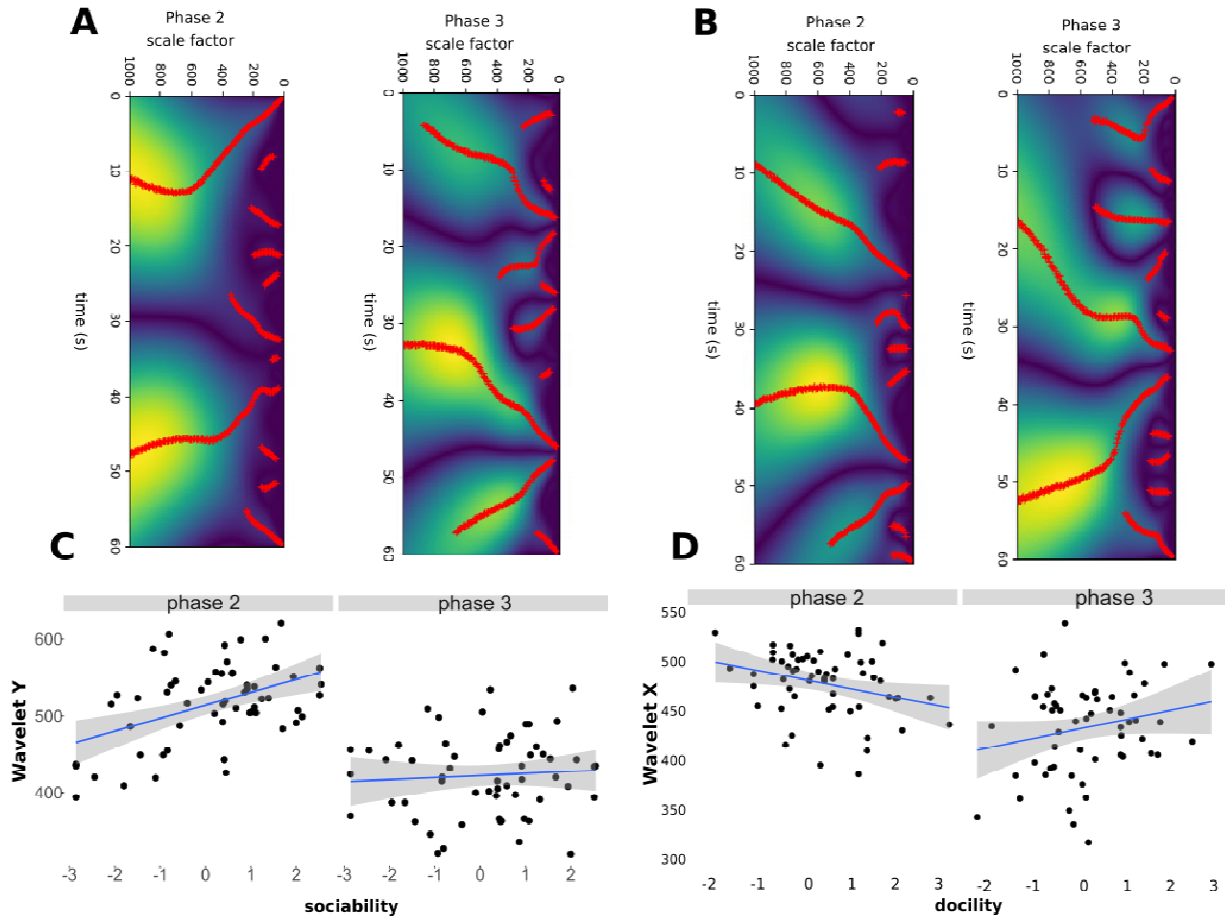
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Figure 1: Corridor test. A. Top view of the focal sheep and the social stimuli in the corridor (example image extracted from video data). B. schematic representation of experiments phases 1, 2 and 3. C. Image of the FMCW radar frontend (phot credit AD). Each rectangle corresponds to rectangular patch (Haderer et al., 2008). D. Example of position estimations of a sheep over time after removing the clutter and normalizing the estimated value.

Figure 2: Analyses of behavioural classes. A. Distribution of the four behavioural classes after a Gaussian Mixture Model. B. Frequency of behavioural classes during phase 2 and phase 3 of the corridor test. C. Correlation between the proportion of time spent in slow movements and the sociability score of sheep during phase 2 and 3 (see details of models in Table 3). D. Correlation between the proportion of time spent in slow movements and the sociability score of sheep during phase 2 and 3 (Table 3). N = 64 sheep.

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Figure 3: Wavelet analyses. A. Example of wavelet transform for lateral movements (X). Red dots correspond to the detection of a change in the displacement at scale factor and time position (i.e., a local maximum of the wavelet transform of the signal position). B. Example of wavel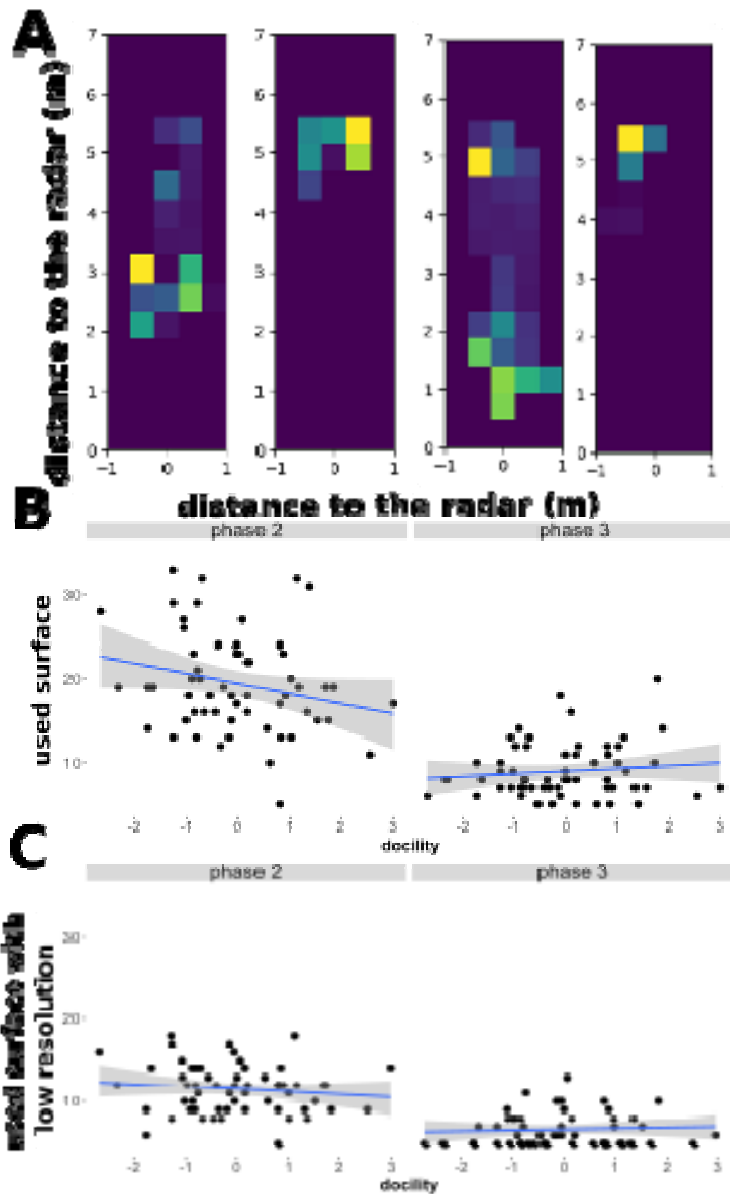et transform for longitudinal movements (Y). C. Relationship between the number of local maxima (red dots in Figures A and B) in the wavelet extraction and the degree of sociability of sheep during phases 2 and 3. D. Relationship between the number of wavelets and the degree of docility of sheep during phases 2 and 3. See details of models in Table 4. N = 64 sheep.
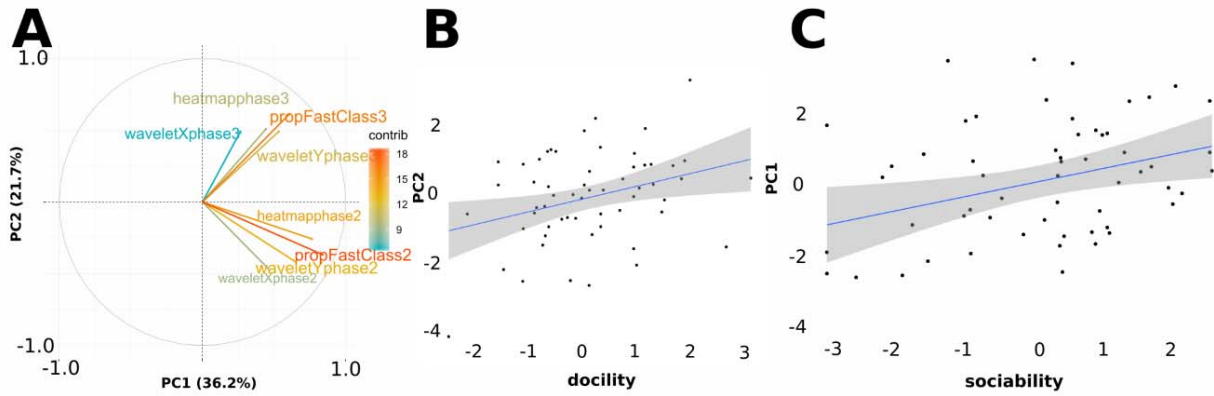
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Figure 4: Heatmap analyses. Relationship between the number of zones occupied by the lambs and the degree of docility in phase 2 and phase 3. A. Low spatial resolution grid (cell dimension: 0.6 x 1m). B. High spatial resolution grid (cell dimension: 0.44 x 0.40 m). Top: examples of heatmaps. Bottom: Correlations. See details of models in Table 6. N = 64 sheep.
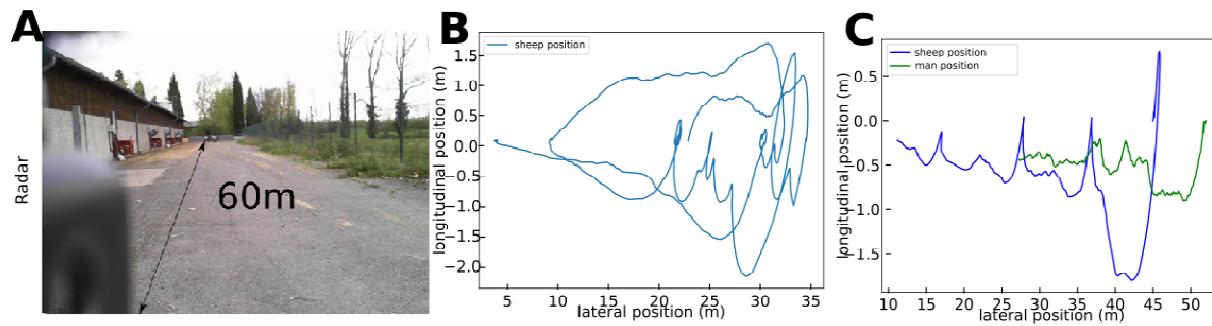
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Figure 5: A. Correlations between the two first components (PCs) of the principal component analysis (PCA). Arrows represent the eight behavioural variables on PC1 (movement speed) and PC2 (movement increase between phases). Contribution of variables to the variance explained is colour coded. Each data point represents the PC1 and PC2 scores of a given lamb (N = 64). B. Relationship between PC1 and sociability. C. Relationship between PC2 and docility. Blue lines represent linear models (see main text). N = 64 sheep.

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714 **Figure 6.** A. Picture of the outside corridor used for radar tracking of a sheep. The radar
715 was positioned 60m from the end of the corridor. B. Example of trajectory of a sheep
716 derived from radar data. C. Example of trajectory derived from radar data of a sheep
717 (red) and a man (green) to induce the sheep movement.

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720 **Supplementary materials**

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722 **Data S1:** Raw trajectories obtained from radar and video for each sheep.

723

724 **Table S1:** Model selection for behavioural class analyses. Null model, best model,

725 second and third best models are displayed.

Variables	AIC	Delta AIC	Weight
age x phase + weight x phase + docility x phase + sex x phase + sociability x phase	5423.774	0	9.92E-01
age x phase + weight x phase + docility x phase + sociability x phase	5433.82	10.04546	6.53E-03
age x phase + weight x phase + docility x phase + sex + sociability x phase	5436.306	12.5314	1.88E-03
Age x phase + docility x phase + sex x phase + sociability x phase	5447.138	23.36415	8.37E-06

726

727 **Table S2:** Model selection for X wavelet analyses (latitudinal movements). Null model,

728 best model, second and third best models are displayed.

Variables	AIC	Delta AIC	Weight
age x phase + weight x phase + docility x phase + sex + sociability x phase	1170.346	0	5.93E-01
age + weight x phase + docility x phase + sex + sociability x phase	1173.937	3.591115	9.85E-02
age x phase + weight + docility x phase + sex + sociability x phase	1174.289	3.942563	8.26E-02
age x phase + weight + docility x phase + sex + sociability	1174.586	4.239789	7.12E-02

729

730 **Table S3:** Model selection for Y wavelet analyses (longitudinal movements). Null model,

731 best model, second and third best models are displayed.

Variables	AIC	Delta AIC	Weight
age x phase + weight x phase + docility x phase + sex + sociability x phase	1189.577	0	5.73E-01
age x phase + weight x phase + docility + sex + sociability x phase	1193.051	3.474946	1.01E-01
age x phase + weight + docility x phase + sex + sociability x phase	1193.325	3.748755	8.79E-02
age + weight x phase + docility x phase + sex + sociability x phase	1193.374	3.797822	8.57E-02

732

733 **Table S4:** Model selection for heatmap analyses (low spatial resolution). Null model,

734 best model, second and third best models are displayed.

735

Variables	AIC	Delta AIC	Weight
weight x phase + sociability x phase	544.1552	0	1.35E-01
weight x phase + sex x phase + sociability x phase	546.3065	2.151297	4.61E-02
sex x phase + sociability x phase	546.376	2.220815	4.46E-02
weight x phase + sociability x phase + docility x phase	546.569	2.413782	4.05E-02

736

737 **Table S5:** Model selection for heatmap analyses (high spatial resolution). Null model,

738 best model, second and third best models are displayed.

739

Variables	AIC	Delta AIC	Weight
age + docility x phase + weight x phase + sociability	664.2827	0	0.058719217
age + docilty x phase + weight + sociability	664.9303	0.6476525	0.042476067

age + docility x phase + sociability x phase	665.5479	1.2652317	0.031191675
docility x phase + weight x phase + sociability x phase	665.8718	1.5891709	0.026527492

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