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1 **FRONT MATTER**

2

3 **Title**

4 Mechanical spectroscopy of insect swarms

5

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15

16

17 **Abstract**

18 Social animals routinely form groups, which are thought to display emergent, collective behavior.
19 This hypothesis suggests that animal groups should have properties at the group scale that are not
20 directly linked to the individuals, much as bulk materials have properties distinct from those of
21 their constituent atoms. Materials are often probed by measuring their response to controlled
22 perturbations, but such experiments are difficult to conduct on animal groups, particularly in the
23 wild. Here we show that laboratory **midge** swarms possess emergent continuum mechanical
24 properties, displaying a collective viscoelastic response to applied oscillatory visual stimuli that
25 allows us to extract storage and loss moduli for the swarm. We find that the swarms strongly
26 damp perturbations, both viscously and inertially. Thus, unlike bird flocks, which appear to use
27 collective behavior to promote lossless information flow through the group, our results suggest
28 that **midge** swarms use it to stabilize themselves against environmental perturbations.

29

30 **MAIN TEXT**

31

32 **Introduction**

33 Acting collectively is widely thought to endow animal groups with a range of benefits (1-
34 3). Groups are, for example, thought to be better able to sense and respond to stochastic and
35 uncertain environments than individuals (4). They may exploit collectivity to migrate (5,6),
36 forage (7), and build (8,9) more efficiently. And the much-vaunted ‘wisdom of the crowd’ effect
37 suggests that groups as a whole are more knowledgeable than any single individual (10). There
38 are thus significant incentives for understanding what group-level effects are possible and how
39 and why they arise, both to deepen our general understanding of complex, interacting systems
40 and to exploit collectivity in engineered systems (11,12). These goals can be addressed by
41 building models, often grounded in statistical physics (3,13,14).

42 Such models typically posit a set of individual-level interactions that when scaled up
43 produce group structure and function. Observationally, however, one can only measure the
44 outcome of any such interaction rules—and since many different interactions can lead to very
45 similar group-level behavior (1), trying to recover the rules to validate models requires the
46 solution of a difficult, and likely ill-posed, inverse problem (15). Instead, we here work at the
47 group level and directly consider the emergent properties of the aggregation. Rather than
48 passively observing only group pattern and morphology, however, which contain little precise
49 information (1), we take inspiration from materials testing and characterize the group response to
50 a controlled applied stimulus (16-18). This approach allows us to extract emergent group
51 properties that are not directly linked to the characteristics of the individuals (16,19), much as
52 bulk materials have well defined properties that are distinct from those of their constituent atoms.

53 Here, we show that at a macroscopic level, when driven by an oscillatory visual cue,
54 swarms of the non-biting midge *Chironomus riparius* respond as if they are viscoelastic. More
55 particularly, comparing the effective storage and loss moduli of the swarm, we find that the
56 swarms are dominated by viscous and inertial damping. We also show that these results are
57 reproduced by a simple stochastic model for the swarm where the visual system of the midges is
58 not explicitly described. Our results suggest that collective behavior in midge swarms serves to
59 provide stability and robustness against environmental perturbations, consistent with their
60 biological function and in contrast to other collective systems such as bird flocks and fish
61 schools.

62 63 **Results**

64 **Controlled dynamic stimuli for midge swarms**

65 Providing controlled stimuli to an animal group like a swarm is more challenging than for a
66 normal material (16,18,20). One way to do so would be to confine the group in a container and

67 apply a true mechanical stress (16). Such an experiment, however, often drives the animals far
68 from their normal biological circumstances, and so is difficult to interpret in terms of the
69 undisturbed group dynamics. Here, we instead harness a natural biological response to a more
70 typical environmental stimulus. We study mating swarms of the non-biting midge *Chironomus*
71 *riparius*, which nucleate in the wild above ground-based visual features known as swarm markers
72 (21,22). These markers tend to localize swarms even though the motion of individual midges is
73 highly convoluted (Fig. 1A). Previously, we showed that moving the swarm marker exerts an
74 effective stress on the swarm, and that quasi-statically separating two initially contiguous swarm
75 markers can pull an existing swarm apart into two stable smaller swarms (18). We observed a
76 mutual attraction of the two resulting sub-swarms when they were not too far apart, suggesting
77 the existence of an effective elastic modulus for the swarm as a whole. However, since the
78 effective stress applied to the swarms by the marker was unknown, we could not measure this
79 modulus. Here, we go beyond these quasi-static measurements by oscillating the swarm marker
80 (Fig. 1B) in analogy with dynamic mechanical spectroscopy experiments (23), circumventing the
81 problem of the unknown stress and allowing us to extract group-level ‘material properties’ of the
82 swarm. Further details of our experiments are provided in the Methods section.

83

84 **Bulk swarm response**

85 When we oscillate the swarm marker sinusoidally at moderate frequencies f and amplitudes A_M ,
86 we find that the swarm moves along with the marker. This effect is most clearly seen in $X_S(t)$, the
87 time-dependent phase-averaged position of the swarm center of mass along the axis of oscillation
88 (Fig. 1C). The swarm tracks the marker and moves at the same frequency, albeit with a smaller
89 amplitude and a phase lag. By fitting this phase-averaged swarm response with a sinusoid, we can
90 extract its amplitude A_S . This amplitude varies linearly with the amplitude of the marker
91 oscillation A_M (Fig. 1D), allowing us to use linear response theory to characterize the driven
92 swarm behavior (23).

93

94 **Vertical variation of the swarm response**

95 Focusing only on the center of mass can hide the details of how the stimulus (that is, the
96 movement of the marker) modulates the swarm. For example, information about external
97 predators has been observed to propagate as a traveling wave through bird flocks rather than
98 affecting all the birds at once (24). **One might therefore expect that the response of the swarm**
99 **ought to depend on the distance from the marker, since it is the source of the stimulus.** To test this
100 hypothesis we looked at lateral slabs **of the swarm, defined as volumes of the swarm that extend**

101 over the full range of the horizontal coordinates x and y in the swarm but only over a small range
102 in the vertical coordinate z (see Materials and Methods), allowing us to retain aspects of the
103 group-level response rather than considering only individuals. We studied the phase-averaged
104 behavior of these slabs as a function of the vertical distance z away from the marker, where $z=0$
105 lies on the marker (Fig. 2A). Each of these slabs extends over the full range of x and y in the
106 swarm but only over a small range in z . Just as for the swarm as a whole, these slabs oscillate at
107 the same angular frequency ω as the marker and are well fit by sinusoidal functions of the form
108 $A_S(z)\sin(\omega t - \phi)$ (Fig. 2A); but the phase-averaged amplitude $A_S(z)$ and the phase lag $\phi(z)$ are
109 functions of z (Fig. 2B and C). For both the amplitude and phase, there is a region at the bottom
110 of the swarm near the marker where the swarm response is rigid and almost independent of z .
111 From roughly 1/3 of the total height of the swarm upward, however, $A_S(z)$ decays and ϕ increases
112 with increasing z (Fig. 2B and C). We attribute the finite phase shift close to the marker to the
113 non-direct coupling between the marker and the swarm (since the effective stress is not a contact
114 stress), and treat it as a net phase difference experienced by the entire swarm.

115 Above the bottom, rigid region, the behavior is suggestive of a damped traveling shear
116 wave propagating through the swarm (Fig. 2D). Since, as noted above, the amplitude of the
117 swarm response is linear in the driving amplitude, we assume that the swarm deformation is also
118 linear in the (unknown) effective stress applied by the marker. Hence, we model the swarm as a
119 general linear stress-strain material (23). We note that by treating the stimulation applied by the
120 marker as a stress, we are implicitly making a continuum assumption for the swarms. Although
121 this assumption is difficult to evaluate independently, since we do not know the relevant internal
122 length scales in the material, it is reasonable given that the laterally averaged deformation of the
123 swarm is smooth in z (Fig. 2D). We can then borrow insight from the medical imaging
124 community, where shear waves are excited in tissue by direct contact or ultrasound and the wave
125 characteristics are used to extract its material properties (25,26). The time-dependent amplitude S
126 of a damped shear wave propagating in the z direction can be written as

$$127 \quad S(z,t) = S_0 e^{-k_i z} \cos(\omega t - k_r z), \quad (1)$$

128 where S_0 is an overall constant (so that $A_S(z) = S_0 e^{-k_i z}$) and k_r and k_i are the real and
129 imaginary parts, respectively, of a complex wavenumber k^* . This simple model predicts that $A_S(z)$
130 should decay exponentially with z and that ϕ should increase linearly with z . Both of these
131 predictions are compatible with our measurements (Fig. 2B and C).

132

133 **Effective material properties of midge swarms**

134 Fitting the dependence of $A_S(z)$ and $\phi(z)$ on z allows us to determine k^* , which in turn allows us to
135 extract the mechanical response properties of the swarms. In particular, k^* is related to the
136 complex shear modulus $G^* = G' + iG''$ by $k^* = \sqrt{\rho\omega^2/G^*}$, where ρ is the material
137 density, which we estimate here as the product of the typical mass of a midge (roughly 2 mg) and
138 the midge number density. For a viscoelastic material, the storage modulus G' (that is, the real
139 part of G^*) measures the elastic energy stored in the shear wave, while the loss modulus G'' (that
140 is, the imaginary part of G^*) measures the energy that is dissipated as the wave propagates.
141 Assuming a uniform ρ , we find that both G' and G'' are nonzero (Fig. 3A and B), so that the
142 swarms respond as if they are fully viscoelastic. Intriguingly, G' is negative and varies
143 quadratically with frequency, suggesting that the behavioral response of midges to the motion of
144 conspecifics endows the swarms with an effective inertia (26). A negative G' also implies both a
145 long wavelength and a rapid attenuation, meaning that the swarm as a whole strongly damps the
146 shear wave. We can also measure the dispersion relation for the shear-wave speed (Fig. 3C),
147 which increases linearly with the driving frequency and is of the same order of magnitude as
148 typical midge velocities (27).

149 To relate the storage and loss moduli to static material properties such as elasticity G_0 and
150 viscosity η , a constitutive law is needed. Standard models of linear viscoelastic materials that
151 characterize material response via a combination of purely elastic and purely viscous elements,
152 however, cannot reproduce the negative storage modulus we observe (23). By adding an
153 additional effective inertial mass, however, we can capture this behavior (26). In particular, if we
154 model the swarm response as an elastic element and a viscous element connected in parallel (a
155 Kelvin-Voigt model) with an additional inertial mass connected in series, we would expect to
156 find $G' = G_0 - \omega^2 G_M$ and $G'' = \omega\eta$, where G_M is a measure of the effective inertia of the
157 swarm (26). These forms fit our data very well (Fig. 3A and B), suggesting that this simple mass-
158 spring-damper model accurately captures the emergent mechanical properties of the swarms. **The**
159 **elasticity of the swarm can be seen as a manifestation of its internal cohesion, and the viscosity as**
160 **its resistance to flow.**

161 For our swarms, we find $G_0 = 1.7 \pm 7 \mu\text{Pa}$, $\eta = 35.8 \pm 0.2 \mu\text{Pa s}$, and $G_M = 29.5 \pm 0.2 \text{ mg/mm}$.
162 The ratio G''/G_0 is a measure of the degree of damping in a material (23), with the inertial
163 contribution removed (26). For our swarms, this ratio ranges from 3 to 62, showing that they are
164 strongly damping.

165

166 Stochastic modeling

167 Our experimental results suggest that swarms possess an effective viscoelastic modulus that
168 emerges from interactions between the individuals, with midges high in the swarm responding
169 the motion of those just below them rather than independently to the movement of the marker
170 itself. However, there is a possibility that the effects we observe may arise from such individual
171 visual processing when combined with parallax and possible optomotor response (28). In this
172 case, the viscoelasticity we see would be the result of the particular visual stimulus and not a
173 generic property of the swarms.

174 To address this question, we turned to the stochastic swarm model of Reynolds et al. (29),
175 which has been shown to reproduce a plethora of recent observations for midge swarms (30).
176 Importantly for our purposes, this model makes no assumptions about the specific nature of the
177 sensory systems of the midges, and so perturbing the model swarms is agnostic as to the physical
178 nature of the perturbation. **Midges in this model are treated as simple self-propelled point**
179 **particles. Interactions between the individuals are not explicitly described; rather, their net effect**
180 **is subsumed into a harmonic restoring force, since experimental observations have suggested that**
181 **to leading order midges appear to be tightly bound to the swarm itself but weakly coupled to each**
182 **other inside it (31).**

183 In the model, the positions \mathbf{x} and velocities \mathbf{u} of midges are given by the solutions of the
184 stochastic differential equations

$$185 \quad \begin{aligned} du_i &= -\frac{u_i}{T} dt + \langle A_i | \mathbf{u}, \mathbf{x} \rangle dt + \sqrt{\frac{2\sigma_u^2}{T}} dW_i(t) \\ dx_i &= u_i dt \end{aligned} \quad (2)$$

186 where the subscripts denote Cartesian components, T is a velocity autocorrelation timescale, σ_u is
187 the root-mean-square speed, and $dW(t)$ is an incremental Wiener process with correlation
188 property $\overline{dW_i(t)dW_j(t+\tau)} = \delta(\tau)\delta_{ij}dt$. **Although all three Cartesian directions in the model are a**
189 **priori equivalent, we label the x_3 direction as z in analogy with the experiments; note that the**
190 **point $z=0$ lies at the center of mass of the swarm.** The first term is a memory term that causes
191 velocity fluctuations to relax back to their (zero) mean value. The second term, the mean
192 conditional acceleration **that expresses the effective restoring force that binds individuals to the**
193 **swarm, is given in spherical coordinates by**

$$194 \quad \begin{aligned} \langle A_1 | \mathbf{u}, \mathbf{x} \rangle &= \cos(\hat{\theta})\sin(\hat{\phi})A_s \\ \langle A_2 | \mathbf{u}, \mathbf{x} \rangle &= \sin(\hat{\theta})\sin(\hat{\phi})A_s \\ \langle A_3 | \mathbf{u}, \mathbf{x} \rangle &= \cos(\hat{\phi})A_s \end{aligned}$$

195
$$A_s = -3r \frac{\sigma_u^2}{\sigma_r^2} \left[\sin \hat{\varphi} \sin \varphi \cos(\hat{\theta} - \theta) + \cos \hat{\varphi} \cos \varphi \right] \quad (3)$$

196 where r is the radial distance from the swarm center, θ and φ are the polar and azimuthal angles
 197 of the position vector, $\hat{\theta}$ and $\hat{\varphi}$ are the polar and azimuthal angles of the velocity vector, σ_r is the
 198 root-mean-square size of the swarm, $x_1 = r \cos \theta \sin \varphi$, $x_2 = r \sin \theta \sin \varphi$, $x_3 = r \cos \varphi$,
 199 $u_1 = s \cos \hat{\theta} \sin \hat{\varphi}$, $u_2 = s \sin \hat{\theta} \sin \hat{\varphi}$, $u_3 = s \cos \hat{\varphi}$, and s is the midge's flight speed. The third term
 200 is the stochastic driving noise. Equation (2) is effectively a first-order autoregressive stochastic
 201 process in which position and velocity are assumed to be jointly Markovian. By construction,
 202 simulated trajectories are consistent with spherically symmetric swarms with Gaussian density
 203 profiles and homogeneous (position-independent) Gaussian velocity statistics. **The model**
 204 **contains three free parameters (σ_r , σ_u , and T); here, we set them all to unity as we are primarily**
 205 **interested in qualitative rather than quantitative comparisons.**

206 To test the response of the simulated swarms to perturbations in a way that does not
 207 presuppose a particular behavioral coupling, **we simply force the horizontal position of the swarm**
 208 **center \bar{x} to oscillate along the x_1 axis.** Physically, this corresponds to assuming that the stimulus
 209 acts on individuals only via the effective emergent properties of the swarm rather than directly.
 210 We find that, just as in the experiments, this stimulus propagates away from the center of the
 211 modelled swarm in a way that is consistent with wave motion (Fig. 4). For both the amplitude
 212 $A_S(z)$ and the phase $\phi(z)$, computed in the same way as in the experiments, there is a region close
 213 to the stimulus where the swarm response is rigid and almost independent of z , **the vertical**
 214 **distance to the center of mass.** Above this region, $A_S(z)$ decreases exponentially with height while
 215 $\phi(z)$ increases linearly with height—just as observed for the real midges. Taking the modeling
 216 one step further, we can use the wave amplitude and phase to compute a shear modulus as we did
 217 above. Again in agreement with the experimental observations, the simulated swarms have a
 218 storage modulus G' that is negative at sufficiently high frequencies and scales quadratically with
 219 frequency (Fig. 5A), indicating an effective inertial mass, and a loss modulus G'' that increases
 220 monotonically with frequency (Fig. 5B). Thus, this simple low-order swarm model reproduces
 221 the mechanical properties observed in the experimental swarms while not assuming any response
 222 that is particular to the **midge** visual system.

223

224 **Discussion**

225 Our results demonstrate that **midge** swarms respond to external stimuli so that the swarm
226 as a whole functions as an actively damped material, with both viscous and inertial contributions.
227 Viscoelasticity has been frequently reported in other active systems such as actin networks
228 (32,33). However, the situation here is different since there are no contact interactions between
229 the midges. **A midge swarm thus cannot support an actual mechanical load, in contrast to, for**
230 **example, aggregations of ants that interlock their legs and transmit true mechanical stresses**
231 **throughout the group (16).** The effective viscoelasticity **we observe here** cannot be explained by
232 typical active mechanics. Instead, it must emerge from the behavior of the individuals, **and is**
233 **better interpreted as expressing a transfer of information through the swarm.**

234 This behavioral response could come in two different forms: an independent response of
235 each individual midge to the moving swarm marker, or a collective response of the swarm where
236 the information about the moving marker propagates through the swarm via interactions between
237 the midges. Although we cannot fully rule out some degree of independent response, our
238 measurements strongly suggest that the collective response is dominant. Simple geometric
239 parallax, for example, would also predict a falloff of the response amplitude with height away
240 from the marker, since the motion of the marker appears smaller for midges higher up in the
241 swarm. However, an explanation in terms of parallax alone with no additional behavioral
242 response would not predict the systematic shift of the phase lag with height that we observe.
243 Instead, this observation, when paired with the effective rigidity of the lowest layers of the
244 swarm, suggests a scenario whereby midges at the bottom of the swarm directly perceive the
245 marker and follow it, while midges higher in the swarm follow the motion of the midges below
246 them instead of the marker itself. This scenario is compatible with our stochastic modeling
247 results, where we found that an oscillation of the emergent potential that captures the collective
248 behavior of the swarm led to the same kind of decaying shear waves as we saw in the experiment.
249 Furthermore, when, in our previous studies, we perturbed these swarms with acoustic signals
250 (17), we argued that the response was not collective because there was no phase lag between any
251 individuals — rather, all the midges phase-locked to the driving signal. What we see here is
252 exactly the opposite. Thus, taking this all together, we interpret our results as indicative of an
253 emergent, collective response of the swarm as a whole. We note that such an interpretation also
254 implies that the stimulus we are applying to the swarm indeed allows us to measure an intrinsic
255 property of the swarm—that is, its inherent emergent viscoelasticity—rather than changing the
256 nature of the swarm.

257 When coupled with the strongly damping nature of the effective shear modulus, we are
258 led to the conclusion that collective behavior in **midge** swarms functions to suppress imposed

259 perturbations very efficiently and keep the swarm stable and stationary even in a noisy, stochastic
260 environment, in contrast to bird flocks where collective behavior has the opposite effect and
261 promotes the lossless flow of information (34). These disparate results are consistent with the
262 biological functions of these two types of aggregations. Male midges swarm to provide a mating
263 target for females (21) so that stationarity is desirable, while birds and fish move together in part
264 to enhance their collective safety against predator attacks, so that rapid information transfer is
265 beneficial (24). Our findings thus demonstrate that these *biological* functions are reflected in the
266 *physical* emergent properties of the aggregations and lend further support to the value of
267 continuum descriptions of collective systems (35).

268
269

270 **Materials and Methods**

271 **Midge colony**

272 We maintain a colony of *Chironomus riparius* midges in a transparent cubical enclosure
273 measuring 122 cm on a side (Fig. 1B). The midge enclosure is illuminated on a timed circadian
274 cycle with 16 hours of light and 8 hours of darkness per day. *C. riparius* larvae develop in eight
275 10 liter tanks filled with dechlorinated tap water and outfitted with bubbling air supplies to ensure
276 that the water is sufficiently oxygenated. We provide a cellulose substrate into which the larvae
277 can burrow. The water is cleaned twice a week; after cleaning, the midge larvae are fed crushed,
278 commercially purchased rabbit food. During their time in the breeding tanks midge larvae
279 transform into pupae, and in the last few days of their life cycle the pupae hatch and adult flying
280 midges emerge out of the water.

281

282 **Experiments**

283 Male *C. riparius* midges swarm spontaneously at dusk as part of their mating ritual. In order to
284 position the swarms in the field of view of our cameras, we use a black square plate as a “swarm
285 marker” (21); swarms nucleate above this marker. **Swarms typically have a spheroidal shape that
286 does not vary much from swarm to swarm, and the spatial size of the swarms is set dynamically
287 by the midges based on the number of individuals participating (27).** The swarm marker is
288 attached to a linear stage with a position accuracy of 14 μm (CS Series Belt Drive with NEMA
289 23 Brushless Servo Motor, Newmark Systems) that moves the swarm marker in a sinusoidal
290 fashion with angular frequency $\omega = 2\pi f$ (where f is the linear frequency), amplitude A_M , and
291 maximum speed $v = \omega A_M$. The period of oscillation of the marker is $T = 1/f$. The stage is
292 hardware-synchronized to the imaging equipment. The operating noise of the linear stage does

293 not disturb the midges since it is quieter than the ambient noise due to the air supplies for the
294 breeding tanks.

295 The experimental protocol was as follows: A recording session would start 30 minutes
296 before the onset of swarming with calibration of the cameras (see Imaging and identification).
297 After the onset of swarming we waited till the swarm grew to roughly 20 individuals and started
298 the marker movement. The swarm would be startled by the sudden movement of the marker so
299 we would wait roughly one minute for the swarm start behaving normally again. Subsequently,
300 we would start recording. Multiple separate recordings would be done in such a session, with
301 varying oscillation amplitude and/or frequency of the marker. A recording session finished when
302 the swarm size fell below 20 individuals.

305 **Imaging and identification**

306 We film the swarms with three hardware-synchronized cameras (Point Grey Flea3 1.3 MP Mono
307 USB3 Vision) at 100 frames per second. The midges are illuminated in the near infrared using 20
308 LED arrays that draw roughly 3 W of power each, four of which are placed inside the enclosure
309 with the remaining arrays positioned on top of the enclosure. Infrared light is invisible to the
310 midges, and so will not disturb their natural behavior, but is detectable by our cameras. The three
311 cameras are arranged in a horizontal plane on three tripods, with angular separations of
312 approximately 30 degrees and 70 degrees (Fig. 1B). To calibrate the imaging system, we assume
313 a standard pinhole camera model (36). The camera parameters are determined by fits to images of
314 a calibration target consisting of a regular dot pattern. The calibration target is removed before
315 swarming begins. Between 30,000 and 100,000 frames of data were recorded for each
316 experiment, depending on the driving frequency of the marker; for experiments at lower
317 frequencies, more frames were acquired to record sufficient full periods of oscillation. We
318 performed a total of 29 experiments at varying amplitude and fixed frequencies of $f = 0.3$ Hz and
319 0.4 Hz, and 20 experiments at constant amplitude $A_M = 84$ mm and varying frequency. **In the 49**
320 **swarms we recorded the number of midges ranged from 20 to 70 individuals.** To identify
321 individual midges in the swarm, we first located the midges on each 2D camera frame by finding
322 the centroids of regions that had sufficient contrast with the background, after subtraction of the
323 average background, and were larger than an appropriate threshold size. When possible, we split
324 larger non-symmetrical regions that consisted of the images of two midges. After identification,
325 the 2D locations determined from each camera were stereo-matched by projecting their
326 coordinates along a line in 3D space using the calibrated camera models and looking for (near)

327 intersections (36). For the results presented here, we have conservatively only considered midges
 328 that were seen unambiguously by all three cameras. Although in principle two views are
 329 sufficient for stereo-imaging, in practice at least three cameras are typically required to resolve
 330 ambiguities and avoid ghost midges. Arranging all three cameras in a plane, as we have done
 331 here, can still leave some residual ambiguity; this situation, however, occurs extremely
 332 infrequently, and is more than compensated for by the simpler and superior camera calibration
 333 that can be obtained when all the cameras are positioned orthogonally to the walls of the midge
 334 enclosure. After identifying the 3D positions of the midges at every time step, we reconstructed
 335 their trajectories using a multi-frame predictive particle tracking algorithm (37,38).

336

337 **Data analysis**

338 The time-dependent position of the center of mass $\bar{\mathbf{x}}(t)$ of the swarm is calculated as

$$339 \quad \bar{\mathbf{x}}(t) = \frac{1}{N(t)} \sum_{j=1}^{N(t)} \mathbf{x}_j(t),$$

340 where $\mathbf{x}_j(t)$ is the one-dimensional position (along the axis of oscillation of the marker) of midge
 341 j at time t , and $N(t)$ is the number of individuals in the swarm at time t . We calculated the phase-
 342 averaged position of the center of mass $X_S(t)$ by averaging $\bar{\mathbf{x}}(t)$ over the period of oscillation of
 343 the marker T via

$$344 \quad X_S(t) = \frac{1}{M} \sum_{i=0}^{M-1} \bar{\mathbf{x}}(t + iT), (0 < t < T)$$

345 where M is the duration of the experiment in full periods T . When computing the phase-averaged
 346 position of the center of mass as a function of height $X_S(z,t)$, we binned individuals in 40 mm tall
 347 **horizontal** slabs, spaced 20 mm apart. We fit $X_S(t)$ and $X_S(z,t)$ using functions of the form A_S
 348 $\sin(\omega t - \phi)$ to obtain A_S and $A_S(z)$, the average and height-dependent amplitude of oscillation of
 349 the swarm, respectively, as well as ϕ and $\phi(z)$, the average and height-dependent phase of the
 350 swarm, respectively. Subsequently, we fit $A_S(z)$ and $\phi(z)/\pi$ with functions of the form $S_0 e^{-k_i z}$
 351 and $k_r z/\pi$, respectively, to obtain values for k_r and k_i . The viscoelastic moduli G' and G'' can be
 352 expressed in terms of k_r and k_i as

$$353 \quad G' = \rho \omega^2 \frac{k_r^2 - k_i^2}{(k_r^2 + k_i^2)^2}$$

354 and

$$355 \quad G'' = \rho \omega^2 \frac{2k_r k_i}{(k_r^2 + k_i^2)^2}$$

356 obtained by solving $k_r - ik_i = \sqrt{\rho \omega^2 / (G' + iG'')}$.

357 We approximate the average swarm mass density ρ for each measurement by calculating
358 the average number density in a sphere of radius 100 mm centered at the instantaneous center of
359 mass of the swarm (to avoid edge effects), and subsequently multiplying this average with the
360 typical midge weight of 2.3 ± 0.2 mg. The swarm density varies by up to 30% between
361 experiments and while G' and G'' are independent of ρ , the wave speed is not. **We find that on**
362 **average the standard deviation in G' and G'' for different swarms is roughly 15%.**
363
364

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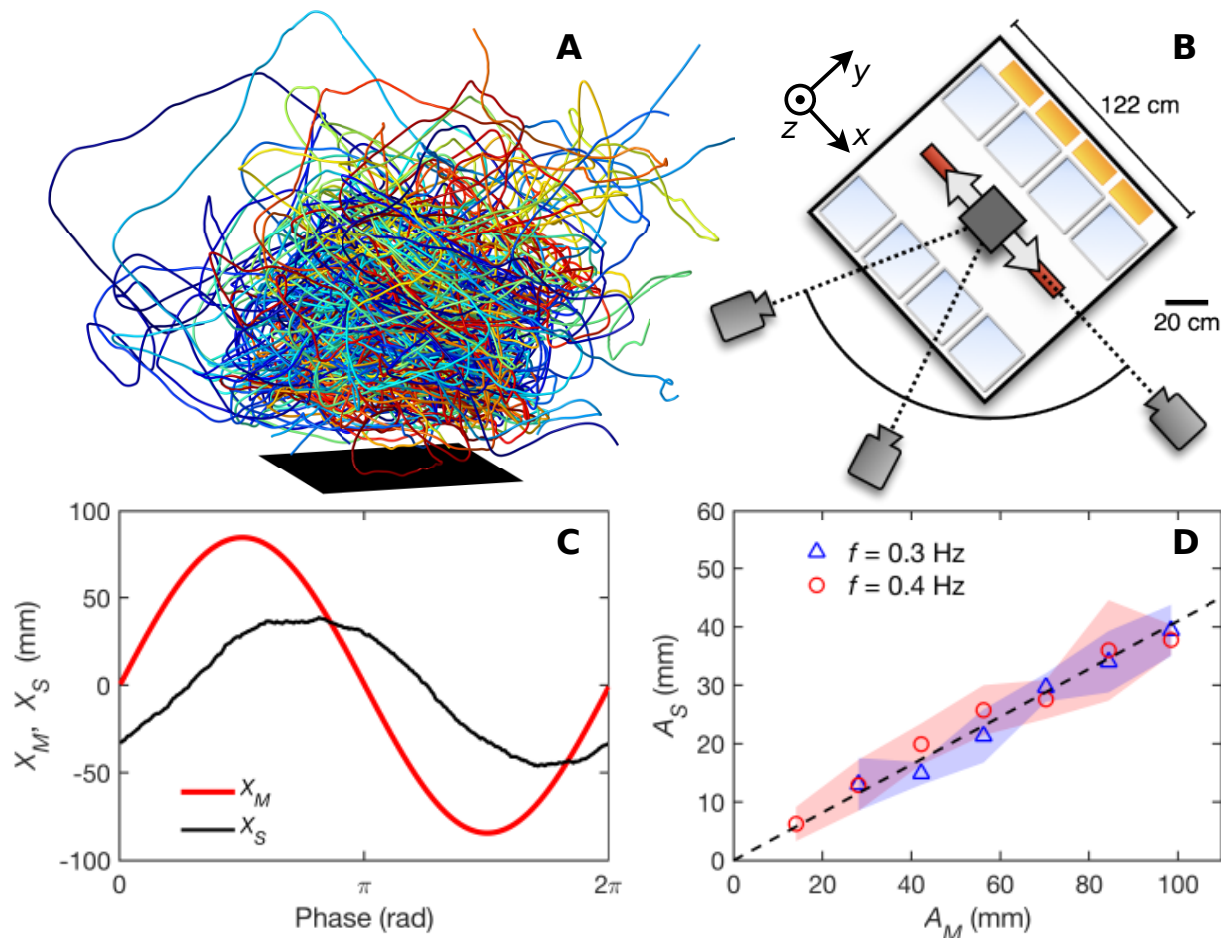
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472 **Figures and Tables**



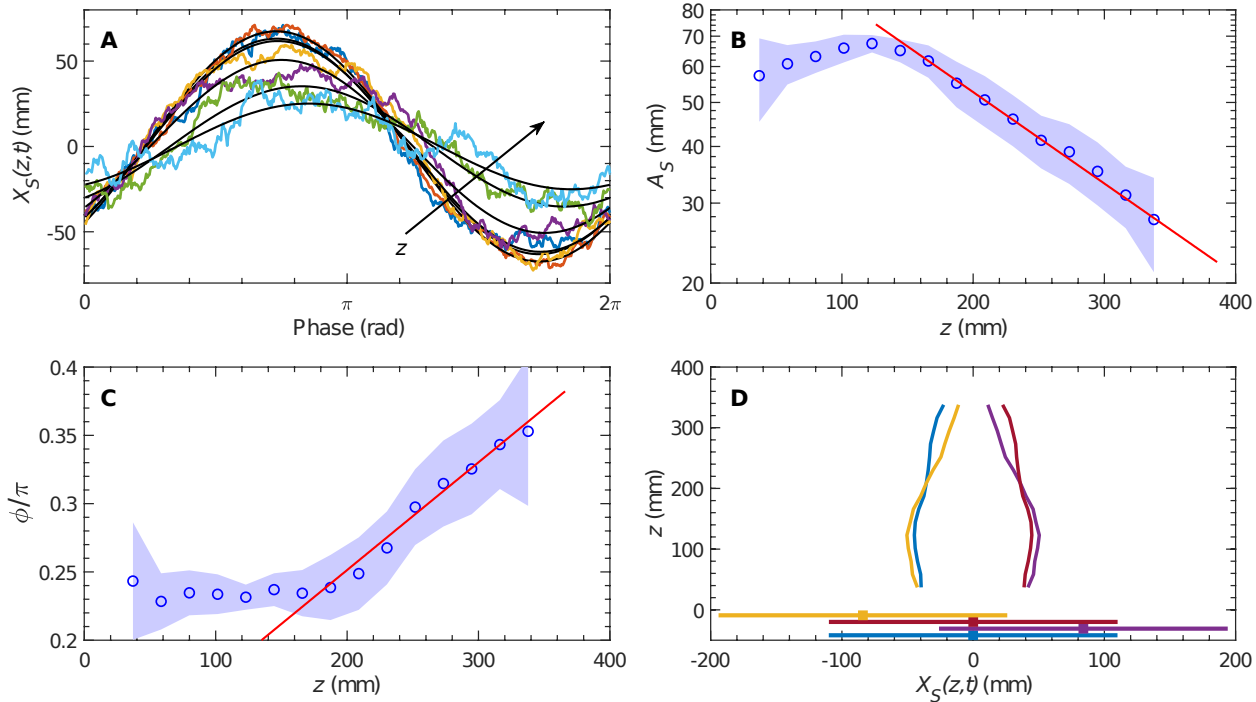
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476 **Fig. 1. Mean swarm response to an oscillating swarm marker.** (A) Trajectories (>40 s long) of
 477 individual midges (each color corresponding to a different midge) are individually convoluted but
 478 remain localized over the ground-based swarm marker (black square). (B) Sketch of our
 479 experimental setup. Swarms form inside a plexiglass cube measuring 122cm on a side and are
 480 imaged using three cameras mounted outside the enclosure. The swarm marker (in dark gray) is
 481 mounted on a linear stage (in red) that can be oscillated over a range of controlled frequencies
 482 and amplitudes along the direction indicated by the white arrows, which we label as the x
 483 direction. z increases vertically from the swarm marker (antiparallel to gravity), with the marker
 484 itself at $z=0$. Also shown are midge development tanks (light blue) and three infrared LED arrays
 485 (yellow; additional arrays on top of the enclosure are not shown). (C) Phase-averaged position of
 486 the center of the swarm marker X_M and the center of mass of the swarm X_S . The swarm center of
 487 mass tracks the sinusoidal motion of the marker, though with a reduced amplitude and a phase
 488 lag. (D) The amplitude of the swarm center-of-mass motion A_S as a function of the amplitude of

489 the marker motion A_M for two different oscillation frequencies, showing a linear relationship
 490 between the two. The shaded area shows the standard error of the mean.

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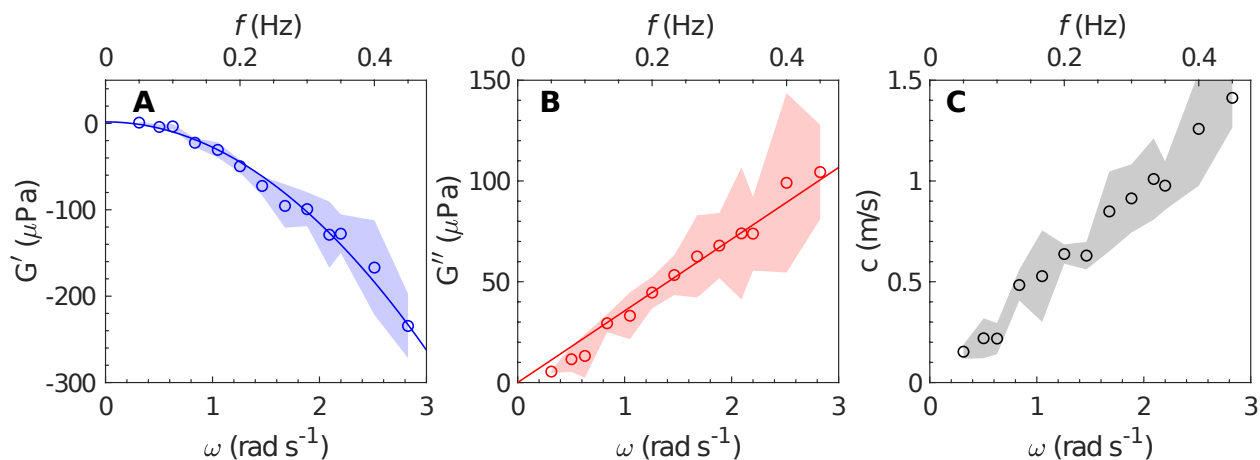


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495 **Fig. 2. Height-dependent swarm response for a fixed amplitude of $A_M = 84$ mm.** (A) Phase-
 496 averaged mean position of laterally averaged slabs of the swarm $X_S(z, t)$ at different heights z
 497 above the marker. As z increases, the amplitude of the swarm motion decreases. Black solid lines
 498 are sinusoidal fits. For clarity, we only show the response for a subset of z values (80, 123, 166,
 499 209, 295, and 338 mm). (B) The amplitude $A_S(z)$ of $X_S(z, t)$ as a function of z . The shaded area
 500 shows the 95% confidence interval, and the red line is an exponential fit. The vertical axis is
 501 logarithmic. (C) The phase lag ϕ (in units of π) between X_M and $X_S(z, t)$ as a function of z . The red
 502 line is a linear fit. (D) Vertical profiles of $X_S(z, t)$ at **four fixed** phases of the driving, revealing the
 503 **shape of the traveling shear wave. Unlike in (A), where each $X_S(z, t)$ curve has fixed z but variable**
 504 **t , here each curve has fixed t but variable z . The horizontal colored lines at the bottom of the**
 505 **figure show the time-dependent position of the swarm marker corresponding to each of the**
 506 **profiles.**

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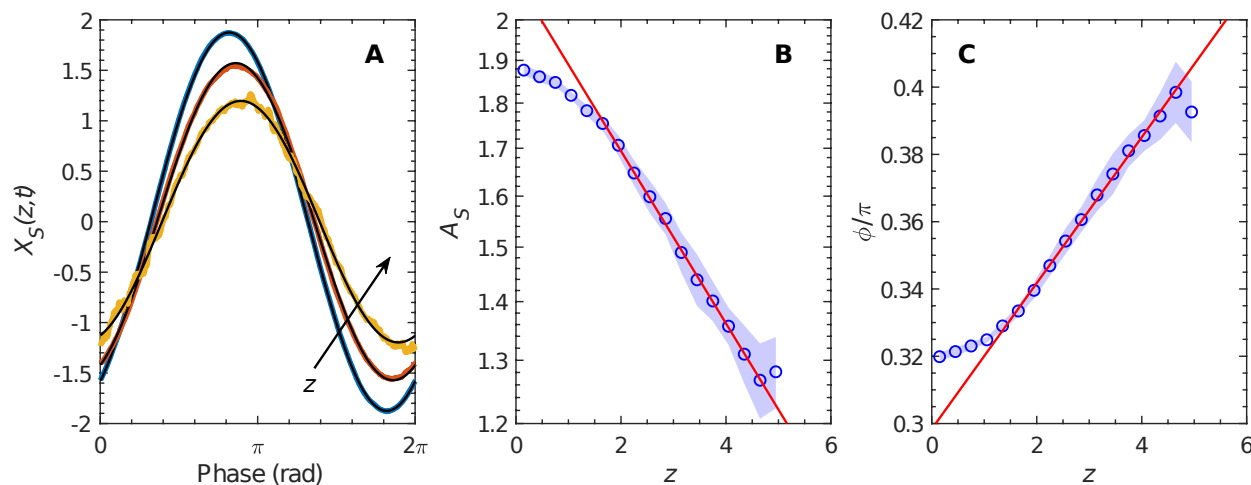
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511 **Fig. 3. Swarm material properties.** (A) Storage modulus G' as a function of driving frequency,
 512 reported for both angular frequency (bottom axis) and linear frequency (top axis), for a fixed
 513 amplitude of $A_M = 84$ mm. The solid line is a parabolic fit. (B) Loss modulus G'' as a function of
 514 frequency for the same data as in (A). The solid line is a linear fit. (C) Dispersion relation
 515 relating the shear wave speed c and the driving frequency. For all panels, the shaded areas show
 516 the standard error of the mean and are the result of averaging over different swarming events.



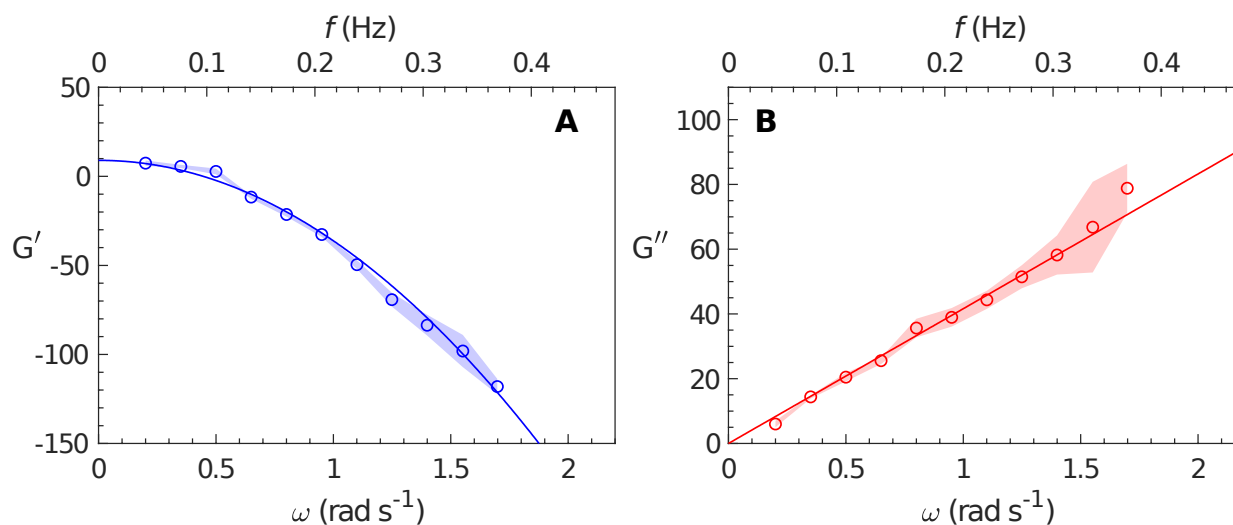
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518 **Fig. 4. Response of a swarm model.** (A) Phase-averaged mean position of laterally averaged
 519 slabs of the swarm model $X_S(z, t)$ at different vertical distances z from the swarm center, where
 520 the oscillating perturbation is applied along x . As z increases, the amplitude of the swarm motion
 521 decreases. Black solid lines are sinusoidal fits. The amplitude of the oscillation of the center of
 522 attraction is 2 and the frequency of oscillation is 0.65 rad s^{-1} . (B) The amplitude $A_S(z)$ of $X_S(z, t)$
 523 as a function of z . The shaded area shows the 95% confidence interval. The red line is an
 524 exponential fit. The vertical axis is logarithmic. (C) The phase lag ϕ (in units of π) between the
 525 oscillation of the swarm center and $X_S(z, t)$ as a function of z . The shaded area shows the 95%

526 confidence interval, and the red line is a linear fit. Results are shown for case where all model
527 parameters (σ_r , σ_u , and T) are set to unity in a.u.

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531 **Fig. 5. Model swarm material properties.** (A) Storage modulus G' of the swarm model as a
532 function of driving frequency, reported for both angular frequency (bottom axis) and linear
533 frequency (top axis), for a fixed amplitude of 2 and swarm density of 1. The solid line is a
534 parabolic fit. (B) Loss modulus G'' as a function of frequency for the same data as in (A). The
535 solid line is a linear fit. For all panels, the shaded areas show the standard error of the mean.

536 Results are shown for case where all model parameters (σ_r , σ_u , and T) are set to unity in a.u.

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