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Scaling and vibrational signals: potential semantic elements in termites

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Abstract

Semantics, or the exchange of meaning in communications, is an essential characteristic of human language that is also present in other species such as monkeys or squirrels and in social insects such as bees. The fundamental unit of semantic communication is the assignment of distinct signals to denote particular elements. Here we report experiments suggesting that vibrational signals of termites encode different responses in front of different stimuli, complying with the elementary blocks of semantic communication. Moreover, we show that the energy statistics of these signals are power-law distributed rather than stochastic. This suggests intriguingly an ordered structure of the temporal vibrational patterns of termites, reminiscent of biological complex systems

1 Introduction

Non-human semantics is becoming a prominent research topic, especially after the irruption of Large Language Models (LLM) that are at the core of modern artificial intelligence and chatbots [39, 15, 21]. Although these technological innovations operate within the framework of human language, their speech is computer-generated. At the same time, the study of many other aspects of languages that reflect universal physical properties is gaining momentum. These include scaling and critical behaviour where long-range correlations between events, symbols, or words decay as power-laws with distance, rather than exponentially. This suggests not only non-randomness but also self-organized processes [11, 22, 20].

Semantic communication involves using unique signals to represent specific elements to members of a group where messages make sense to all parties [35, 32, 38, 23]. A key biological advantage of semantic communication is that it

allows responding with precision, enhancing survival and adaptive behaviours. The ability to produce signals that semantically represent specific elements is documented in various species, such as in primates [35] and squirrels [6]. These animals access external stimuli and codify them into specific signals, triggering specific responses in their conspecifics. Non-conspecific semantic communication seems to exist as well, for example between humans and their domesticated animals [25].

Regarding social insects, semantic communication was identified in bees in a classic study by von Frisch [41]. In termites, it is documented that they access external stimuli and react accordingly [8, 9, 29]. They are also able to produce vibrations alerting their nestmates about risks [17, 40]. Later, evidence was found for a specific vibrational alarm for pathogenic infections in some termites [34]. However, whether these signals really represent specific elements remains unclear. Could termites engage in semantic communication? Would they be able to access external information, codifying it to their nestmates in a structured and specific, nearly semantic way? Here we explore this issue, verifying whether termites modify their vibrational signals, tailoring these vibrations to the specificity of the stimulus. In doing so, termites could be said to have the basic tools to communicate semantically.

Termites are known to hear, interpret, and use vibrational cues to access valuable information on their surroundings. This ability enables them to react adaptively to external stimuli. For example, these insects can use vibrational cues produced as by-products of their feeding activities to assess food size [10, 18]. Additionally, they rely on vibrational cues to detect and avoid threats, recognizing substrate vibrations caused by ants as they walk [29]. Vibrational cues also help termites to identify and avoid nestmates infected with entomopathogenic fungi [34].

In addition to reflexively reacting to external stimuli, termites can also codify the information they have accessed, translating it into vibratory signals which could be used by their nestmates. When exposed to experimentally inflicted stimuli, such as artificial vibrations and air currents, some termites responded by producing vibratory movements, alerting their nestmates [33]. Nestmates were also alerted by vibratory signals produced by termites exposed to insecticides [24] or to pathogens [2, 26, 34].

The ability of termites to codify external stimuli is remarkably sophisticated, as they can process either highly distinct stimuli or subtle variations of the same stimulus. For instance, some termite species can produce distinct numbers of the same vibratory response according to two discrepant doses of their own alarm scent [5]. They can also modulate these numbers of vibrations in response to increasing doses of an insecticide [24]. These findings collectively highlight

termites' nuanced and finely tuned ability to distinguish variations in stimulus, encoding them into distinct numbers of vibrations.

This codification is effectively transmitted to nestmates, provoking distinct reactions. Vibrational signals produced by disturbed individuals can incite their nestmates to escape, freeze, perform additional vibratory movements [4], or even engage in grooming and trophallaxis [34, 26, 2, 24]. Termites can also use vibratory signals to coordinate defensive actions in their nestmates [12, 13, 33].

Such an ability of termites to codify external stimuli has commonly been observed to involve the repetition of similar vibrational movements, which were globally referred to as drumming or tremulation [16]. Termites repeat either drumming events or longitudinal oscillatory movements ["tremulation" *sensu* 16] according to the stimuli they receive [5, 2, 24]. However, in addition to the ability to repeat vibrations, termites also have the ability to produce distinct types of body shaking movements. For instance, [42], identified and categorized four distinct types of longitudinal oscillatory movements (LOMs) in *Reticulitermes flavipes* in response to two different stimuli. This classification was later validated by [30], providing further evidence of signalling repertoire in termites.

Thus, if termites can both repeat existing signals and produce new ones in response to stimuli, it is reasonable to assume that they might be able to integrate these abilities. In doing so, they would generate unique vibrational signatures in response to distinct stimuli. This approach mirrors the alarm call systems found across the animal kingdom, where simple acoustic or vibratory elements, when combined, consistently elicit specific responses [19, 35].

Here we will test the above hypothesis that termites can employ a similar strategy, combining basic vibrations to form vibratory signatures in response to each type of stimuli. By obtaining favourable evidence for this hypothesis, we argue that termites are equipped with the most basic building blocks of language. To further challenge our hypothesis, we explore the statistics of the energy pulse distribution of termite vibrational signals in order to verify whether they exhibit complex patterns which would pose them far from trivial stochastic processes, a characteristic also found in structured languages [22].

2 Methods

2.1 Termite Collection

Assays were conducted using 15 wild nests of *Constrictotermes cyphergaster* (Blattodea: Isoptera), collected in April 2017 in the Brazilizan "Cerrado", in the municipality of Sete Lagoas, Minas Gerais, Brazil (S 27°19', W 14°44'; altitude 800-900m above the sea level). The colonies were transported to the campus of

the Federal University of Viçosa, in the municipality of Viçosa, Minas Gerais, Brazil, where they were kept under laboratory conditions. Water and food was offered, *ad libitum* during the whole period of the assays.

2.2 Experimental setup

The assays were designed to measure the vibrational reaction exhibited by workers and soldiers of *C. cyphergaster* when they were subjected to different stimuli. To perform the assays, we designed an experimental setup to minimize noise and vibrations from nearby external sources (Figure 1A). This setup, fully described in [27], consisted of a wooden box lined with (approx.) a 5-cm thick layer of glass wool plus an 8-cm thick styrofoam layer (Figure 1C).

In order to acoustically amplify the feeble vibrations exhibited by the termites, we used an arena bearing a flexible floor (so as to mimic a tympanum) as described and tested by [28]. The tympanic arena, consisted of a frame covered by tracing paper as if forming a drum. On the tympanic arena, we placed a lid of a plastic Petri dish ($\varnothing$= 53 mm) to hold the termite individuals to be assayed. The tympanic arena (frame plus Petri dish) was placed inside a wooden box lined with a thick layer of glass wool and styrofoam to reduce external perturbations (Figure 1C). Inside the wooden box, the Petri dish was connected by a hose to the injection chamber placed outside the wooden box. In the injection chamber, we placed each stimulus tested (Figure 1B). Each stimulus was carried to the termites by gently injecting a known volume of air, in the Petri dish, carrying the stimulus odours. Full details regarding the development of this setup can be found in [27].

Termites were observed in the arenas in groups of 15 individuals (12 workers and 3 soldiers). The groups were submitted to various stimuli arranged in the following treatments: (i) empty chamber, thus only air (A), (ii) air + paper (AP), (iii) air + paper + hexane (APH), and (iv) air + paper + hexane extract of soldiers' heads (APHE). For stimulus A, the injection chamber was empty while for the other stimuli, the chamber received a piece of filter paper (7 × 3 mm). For stimuli APH and APHE this piece of paper was loaded with known volume of hexane or soldier's head extract, respectively.

To prepare the soldiers' head extracts (APHE) stimulus, we picked up 20 soldiers from their respective nests. After anaesthetisation with ice, their frontal glands were exposed, immersed in hexane (10 μL per head) and placed in a freezer at 2.4 °C for 24 hours. The resulting extract was then collected with the help of a microsyringe and stored again in the freezer until its use in the assays. From each nest, we prepared only one extract, totalling 15 extracts.

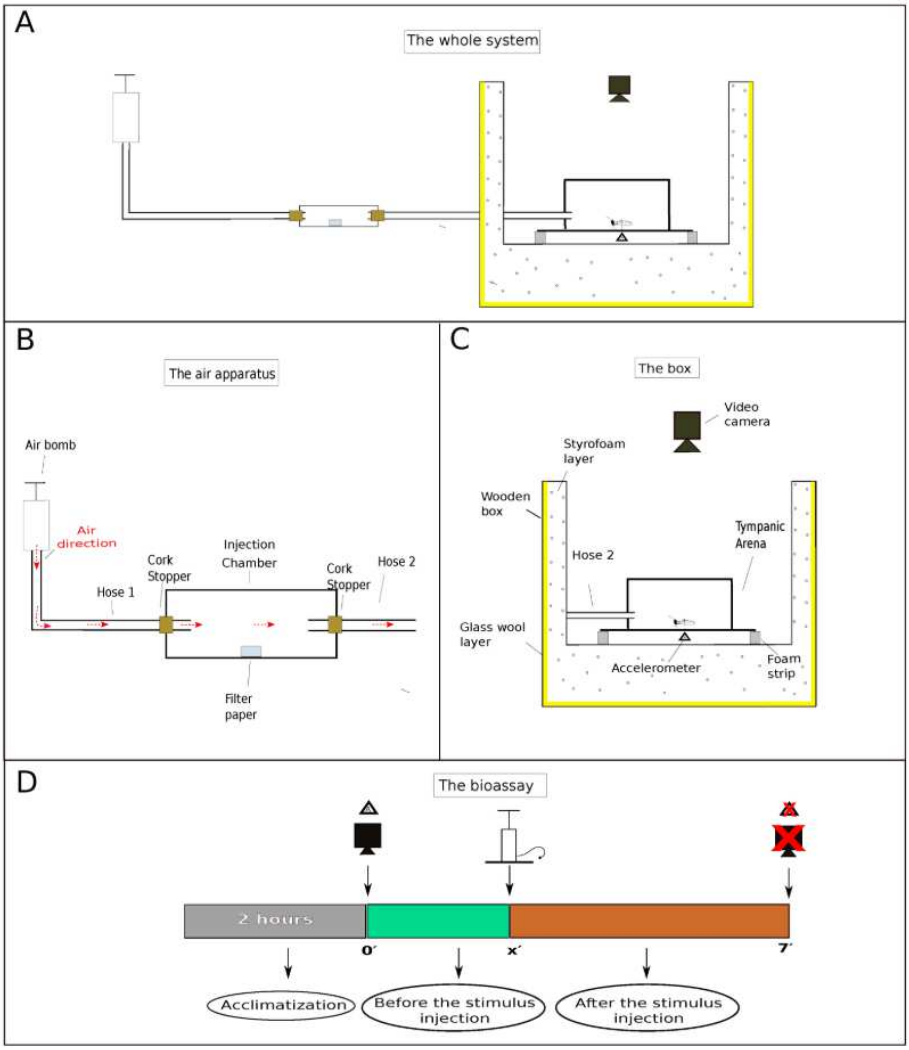


Figure 1: Schematic depiction of the setup designed to measure termite vibrational responses when subjected to different stimuli. **(A)** Global view of the setup, showing an air pump connected by hoses through an injection chamber and to a tympanic arena housed in a wooden box. **(B)** Detailed view of the air pumping system, showing the injection chamber used to house the sources of stimuli. **(C)** Detailed view of the wooden box lined with styrofoam and glass wool to minimise external noise. **(D)** The chronology of each assay: *(i)* each termite was allowed at least 2 h of acclimatization before the beginning of the assays; *(ii)* video and accelerometer recordings start about 2 min before the stimulus injection; *(iii)* after injecting the stimulus, recordings proceeded for another 5 min, totaling 7 min of readings. x' is the exact time at which the stimulus was injected. Original drawing (CC-BY license) [27].

2.3 Accelerometer and datasets

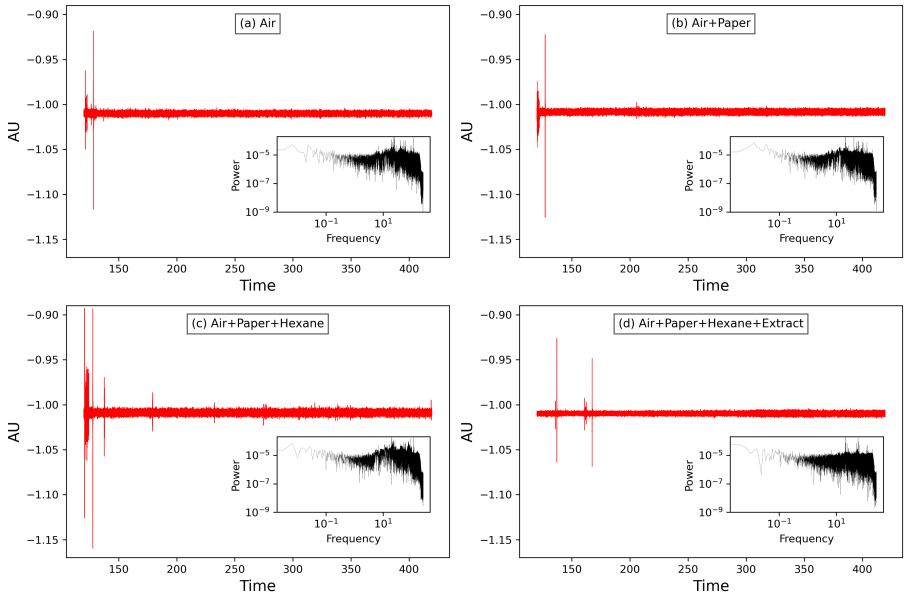


Figure 2: Samples of typical accelerometer temporal measures corresponding to the four treatments (a, b, c, d). Z-axis is shown as the red signal. Insets are their corresponding FFT power spectra. AU are accelerometer units, see text for the conversion to g units.

The accelerometer used in our study is a custom-designed device manufactured by Gulf Coast Data Concepts. It is based on the Model X2-2 USB accelerometer data logger (2013) but modified to have the sensor outside the case while connected to the main unit by means of a shielded cable. In this way, the small sensor could be conveniently attached to the external bottom of the tympanic arena (the tracing paper membrane). The X2-X sensor is the miniature Kionix KXRB5-2050 chip that is capable of detecting 3-axis movements with an up-to 512 Hz sample rate (512 readings per second). The output data is a standard comma-delimited computer-readable CSV file containing information such as time stamp and X, Y, Z data. Raw acceleration data from the logger is recorded to the output file in signed "counts" units that can be converted to g units when dividing the registered data by 13108. Only the Z-axis data was used in our study since this axis contains most of the drumming activity.

We obtained 60 datasets in total, 15 for each of the four treatments (*i.e.*, stimuli) as explained above. We recorded 215,040 readings (512 readings × 60 s × 7 min) per assayed termite group, totaling about 12,840,000 readings = (215,040 readings × 4 stimuli × 15 assays) – (2 missing assays × 215,040

readings) for the whole experiment.

To analyse our datasets, we trimmed the first 120 seconds from each file (marked as green in Figure 1D), as these records contained no data relevant to termite response to the stimuli. After all, the stimuli were applied 120 seconds after the data logger was switched on (marked as brown in Figure 1D). The datasets were also cut at the tail to ensure that all files contained the same number of time records ($N = 153,429$).

2.4 Analytical procedures

Two different analytical procedures were applied to the datasets, after they had been standardised to the same number of time records. First, a Fourier Transform (FFT) was applied to each one of the 60 datasets (15 datasets in each of four treatments) to obtain its respective vibrational profile in the frequency space (insets in Figure 2).

Once the datasets were transformed, they were binned into N-1 equal-sized bins. This was necessary to sum all the 15 data sets from a given stimulus (= treatment), frequency by frequency. Because we had four stimuli, this summation produced four FFT data files, which were then smoothed with average windows of sizes 500, 1000, and 1500 to reduce potential noise. After that, non-parametric tests (Mann-Whitney and Kolmogorov-Smirnov) were applied in order to pairwise compare termite vibratory responses to stimuli ("treatments") against each other. This would help elucidate whether the termites' responses were indeed different across the four stimuli.

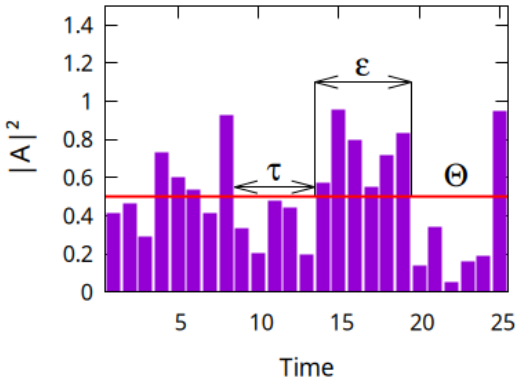


Figure 3: Example of an arbitrary time series showing events of interest above a given threshold value Θ (horizontal red line). τ is the time interval between two successive events that are above Θ, in this case $\tau = 5$. ϵ is the duration of the energy pulse that is above Θ, in this case $\epsilon = 6$. $|A|^2$ measures the amplitude or magnitude of the energy pulses.

The second procedure was performed on each of the same 60 time series used above, but it was done before the FFT was applied. On each temporal datafile we found the average value of the accelerometer readings in the time series and centered the data set at this value as a zero-value. Accelerometer reading values were then squared so that all temporal values were positive, obtaining an effective energy profile of the termites vibrations ($|A|^2$). These new transformed time series contain energy pulses evenly distributed in time (See Figure 3, for a graphical example). We defined an arbitrary but standard threshold value Θ for each time series in such a way that 70% of the energy values fell below this value. For values greater than Θ we measured two new quantities. τ is the inter-event distance between successive energy pulses and ϵ is the duration of each individual energy pulse. We built two frequency tables, one with the probability distribution of τ values and the other for the ϵ values. These tables were plotted in log-log plots in order to identify scaling as power-laws, since such patterns may suggest self-organization, criticality or long-range correlations. Two-parameter power-laws $f_1(x) = ax^b$ and exponentials $f_2(x) = e^{cx}$ were fitted to each of the 60 energy profiles. Two methods were used for the fittings. The first was a non-linear regression analysis with a Levenberg-Marquardt (LM) algorithm where the standard criterium for the best fitting is the highest R^2 value. The second method was the use of maximum-likelihood estimates and the Akaike information criterion (AIC) to find the suggested model that better explained the data.

3 Results

Pairwise non-parametric tests on the summed FFT data, smoothed via (500, 100, 1500) moving average windows, suggest that the four treatments are significantly different from each other (Table 1). That is to say, each of the four stimuli corresponded to a distinct arrangement of vibratory frequencies in the assayed termites (Figure 4).

On the other hand, analysis of the energy profile of the vibration signals, both the inter-events interval τ and the pulse widths ϵ gave mixed results when a LM algorithm was used (Table 2). We found evidence of the presence of power-laws; however the presence of exponential decays was slightly larger than of the power-laws (61.6% of τ time-series and 56.6% of ϵ time-series). It is now well known that regression analysis, even being non-linear, can give misleading results when the number of data points to fit is low, as in our case [7]. We then use a second approach, the use of MLE parameter fitting and AIC model

Table 1: P-values obtained in the non-parametric tests (MW = Mann-Witney; KS = Kolmogorov-Sminorv) performed on the FFT transformed vibratory series of termite responses to four experimental stimuli (only air = A, air + paper = AP, air + paper + hexane = APH and air + paper + hexane extract of soldiers' heads = APHE). Here we test the *H0* hypothesis that the two series under test came from the same population of vibratory responses.

comparison	P-value (MW)	P-value (KS)
A *vs* AP	$\ll 0.00001$	$\ll 0.00001$
A *vs* APH	$\ll 0.00001$	$\ll$ 1E-15
A *vs* APHE	$\ll 0.00001$	$\ll$ 1E-15
AP *vs* APH	$\ll 0.00001$	$\ll$ 1E-15
AP *vs* APHE	$\ll 0.00001$	$\ll$ 1E-15
APH *vs* APHE	$\ll 0.00001$	7.093e-08

Table 2: Power-law and exponential fittings on the effective energy data showing the number of occurrence and their percentage (in parentheses) per treatment and by class (inter-events τ and energy pulses ϵ). PL = power-law, EXP = exponential decay. As usual, model selection is based on the largest regression coefficient(R^2) using a Levenberg-Marquardt non-linear algorithm programmed in R.

Inter-events (τ)	Treatment	PL	EXP	Total
	A	5(33.3)	10(66.6)	15
	AP	6(40)	9(60)	15
	APH	7(46.6)	8(53.3)	15
	APHE	5(33.3)	10(66.6)	15
	Total	23(38.3)	37(61.6)	60
Energy pulse (ϵ)	Treatment	PL	EXP	Total
	A	7(46.6)	8(53.3)	15
	AP	6(40)	9(60)	15
	APH	8(53.3)	7(46.6)	15
	APHE	5(33.3)	10(66.6)	15
	Total	26(43.3)	34(56.6)	60

comparison [7, 3] programmed in R. This procedure suggests that in our data, power-laws (PL) better explain the scaling of energy events when compared to exponential decays (EXP) (See Tables 3 and 4 and Figure 5). We warn that our data span over two logarithmic decades so precaution is in order. For this reason, we consider these results as suggestive evidence rather than a firm fact.

4 Discussion and conclusions

Termites are endowed with a number of communication modes that are essential for maintaining their massive, parallel and highly coordinated collective behaviour. Such a complex display of social activities strongly suggest that communications among them are far from trivial. What sort of information content is transferred among them is mostly unknown. If they do have a code,

Table 3: Akaike AIC model selection with MLE parameter estimation ($x_{min} = 2$) reveal that (PL-AIC < EXP-AIC) suggesting that a power law is a better fit than an exponential decay for the inter-event (τ) time series, for all treatments and all samples. T = Treatment.

NestID	T	PL-AIC	EXP-AIC	NestID	T	PL-AIC	EXP-AIC
N01YCC2017	A	15316.43	19769.45	N02YCC2017	A	13953.65	19320.36
	AP	12501.83	16789.07		AP	11505.30	15358.52
	APH	14146.51	18839.20		APH	15487.22	20088.83
	APHE	12873.92	18096.58		APHE	14319.29	18681.78
N03YCC2017	A	10306.06	13121.94	N04YCC2017	A	14540.91	20660.03
	AP	12765.13	17903.28		AP	14698.72	20113.77
	APH	15209.39	19900.09		APH	11260.77	14717.19
	APHE	12216.94	16476.72		APHE	14411.76	19801.95
N05YCC2017	A	13691.86	18928.69	N06YCC2017	A	14088.32	19251.63
	AP	12337.41	16758.90		APHE	12215.18	16891.72
	APH	13635.73	18584.59		APH	14296.10	19274.36
	APHE	11933.48	16729.50		AP	14754.82	19827.91
N07YCC2017	A	13269.83	17935.36	N08YCC2017	A	14065.05	19192.04
	AP	15764.28	20298.03		AP	15136.52	21561.98
	APH	16776.80	22199.43		APH	16124.10	21359.28
	APHE	12281.56	17387.38		APHE	19535.94	24681.15
N09YCC2017	A	15886.71	20994.35	N10YCC2017	A	16536.42	22605.68
	AP	14572.04	20848.2		AP	17540.19	23962.44
	APH	15660.80	21251.88		APH	15581.13	21306.36
	APHE	16776.82	22803.72		APHE	21174.36	26720.86
N11YCC2017	A	13928.14	18867.95	N12YCC2017	A	16181.02	21512.90
	AP	17445.85	23208.68		AP	13873.45	17284.59
	APH	17813.71	23000.80		APH	17393.59	22322.02
	APHE	15663.84	20515.11		APHE	12868.31	16922.90
N13YCC2017	A	14476.91	19639.34	N14YCC2017	A	13894.16	18573.08
	AP	14774.51	19546.75		AP	14171.85	19437.43
	APH	17477.49	21683.64		APH	16201.53	20842.06
	APHE	11924.81	16557.12		APHE	15649.10	20339.30
N15YCC2017	A	15413.78	19734.95				
	AP	15502.90	20882.17				
	APH	9629.21	12803.00				
	APHE	9959.34	13607.13				

Table 4: Akaike AIC model selection with MLE parameter estimation ($x_{min} = 2$) reveal that (PL-AIC < EXP-AIC) suggesting that a power law is a better fit than an exponential decay for the energy pulse (ϵ) time series, for all treatments and all samples. T = Treatment.

NestID	T	PL-AIC	EXP-AIC	NestID	T	PL-AIC	EXP-AIC
N01YCC2017	A	68258.20	77875.77	N02YCC2017	A	71522.32	79127.75
	AP	77083.14	84064.42		AP	73563.54	81233.49
	APH	73613.11	81337.92		APH	68487.80	78047.15
	APHE	72265.19	81475.77		APHE	72145.55	80112.98
N03YCC2017	A	67872.79	73407.86	N04YCC2017	A	79154.05	89016.66
	AP	79484.83	85985.37		AP	72664.43	82449.49
	APH	67561.77	76924.49		APH	72887.02	77323.48
	APHE	70159.33	78117.24		APHE	72009.59	79050.60
N05YCC2017	A	72548.69	81273.16	N06YCC2017	A	75049.53	81538.29
	AP	79590.68	83827.55		AP	72352.94	81072.78
	APH	73999.17	82219.08		APH	73534.79	79914.33
	APHE	73902.56	81898.60		APHE	76114.29	82716.93
N07YCC2017	A	74375.33	81883.03	N08YCC2017	A	75539.70	82407.57
	AP	73102.58	81932.60		AP	75070.68	81986.18
	APH	72522.50	80693.06		APH	74348.51	81788.41
	APHE	75454.90	83485.98		APHE	72159.21	78664.03
N09YCC2017	A	77932.42	84410.10	N10YCC2017	A	75103.16	82548.77
	AP	75324.56	83480.96		AP	70695.96	81009.44
	APH	79517.95	85345.81		APH	71056.05	79384.50
	APHE	74690.35	82085.04		APHE	78930.39	81447.64
N11YCC2017	A	75091.66	82626.70	N12YCC2017	A	76172.14	89306.98
	AP	76571.58	83040.65		AP	71856.74	77778.42
	APH	73134.39	82880.93		APH	75148.18	84371.67
	APHE	79050.92	85844.19		APHE	73528.94	79307.31
N13YCC2017	A	74689.08	82899.44	N14YCC2017	A	69420.51	79218.26
	AP	75251.95	81154.73		AP	73216.36	81411.55
	APH	77239.95	87884.97		APH	71382.36	79599.33
	APHE	74562.24	81920.91		APHE	70944.93	78908.97
N15YCC2017	A	70621.45	80548.78				
	AP	80479.10	88969.72				
	APH	73070.81	78934.13				
	APHE	74691.86	83887.77				

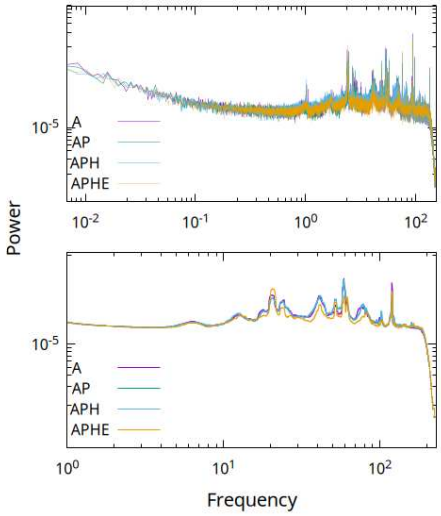


Figure 4: Fourier transforms of the time series for the four treatments. Upper panel shows the plot of the binned data. Lower panel shows the plot of the binned data with a moving average window of size 500.

what kind of code will that be? A common language?

Our results provide favourable evidence supporting the hypothesis that termites combine basic vibrations to form specific vibratory signatures in response to specific types of stimulus.

In fact, each of the four experimental stimuli tested elicited termites to produce distinct FFT spectra (Table 1, Figures 2 and 4). This would suggest that the vibrational patterns produced by these termites were specifically modulated according to the stimulus, thereby generating a unique vibrational signature for each type of stimulus.

These findings contrast with previous observations that vibrations in other termite species could be characterised by a fundamental vibrational frequency [12]. Rather than a characteristic frequency, termites here studied combined different frequencies in response to distinct stimuli (Figure 2), creating specific vibratory signatures in response to each of these. Indeed, even specific vibrational frequencies that are well represented across treatments appear to exhibit subtle shifts depending on the stimulus (Figure 4). This would suggest that these termites do not react in a generic way to any stimulus. Instead, they seem to have the basic tools to tailor their responses to encode specific information.

The termites tested here responded to external stimulation by striking the substrate with their heads and/or abdomens, generating vibrational signals (Figure 2 and 4). Importantly, however, these signals appear not to be merely

a reflexive or random response. Instead, termites appear to actively modulate their vibration, changing its structure depending on the type of stimulus.

Previous studies suggested that the primary coding mechanism of information in termites consisted of producing vibratory signals in a temporal sequence. The signal of termites would be characterized by the number of hits they strike on the substrate per unit of time [5, 12]. That is, termites would produce a signal that could be characterised by a fundamental frequency [14, 37]. Any difference between signals would be due to filtering by the substrate [16, 14].

Our results add a new perspective to this by showing that differences between signals are not uniquely due to the substrate but can be actively produced at the source of the signal. After all, we have the same substrate across all assays and, even so, we observed differences in termite vibratory patterns. That is, termites actively modify the structure of their signals changing the number of hits per unit of time as well as the strength they impose on each hit. This would necessarily produce spectral differences between signals. Since we have observed spectral patterns typically connected to a type of stimulus across various repetitions of our assays (Table 1), we could say that these spectra actually convey information. Thence, the coding mechanism of information in these termites could be said to consist of producing vibratory signals that, rather than differing simply in temporal sequence, differ by their spectral patterns.

By producing unique signals varying the spectral patterns of their vibration, these termites were able to produce precise information about their environmental context. This ability to use unique signals to represent distinct elements is a fundamental requirement to communicate in a semantically structured way [35, 36, 38, 23]. We argue that such signal modulation might equip termites with the most basic building blocks of language. This seems to indicate that termite signalling repertoire is potentially far more "encyclopedic" than previously thought. It seems then conceivable to sustain that termites are equipped with tools that enable them to communicate in a kind of proto-semantical way.

We also report suggestive evidence that the scaling of energy profile of the vibration signals scales as power-laws (Table 4). It is known that correlation between symbols scales as power-laws in formal language theory [20, 11] meaning that these languages are not Markovian that is, not probabilistic in nature. Power-laws may signal the existence of critical behaviour in the statistical physics sense of collective phenomena occurring near phase transitions [1, 31]. In human language, power-laws have also been identified, suggesting that speech generation operates close to criticality [22]. Our results (power-laws scaling) add evidence that collective termite vibrations induced by external stimuli may be indeed part of a non-probabilistic language and that this process is complex and nonlinear. We also believe that further and more refined experiments are desir-

able to explore these aspects in more detail, with respect to potential semantic communication in termites in particular and in social insects in general.

Ethics Statement

All necessary permits were obtained for the described study, which was in accordance with all relevant Brazilian regulations. This includes collecting and transportation permits from IBAMA (The Brazilian Institute for the Environment and Renewable Natural Resources), as well as tacit approval from the Brazilian Federal Government implied by granting the authors the post of Scientific Researcher. Species collected for the present study are neither endangered nor protected, therefore no specific permits were required for laboratory experiments.

Data access

Time series containing termite vibration raw data are available at the FAIR-aligned Harvard Metaverse repository: https://doi.org/10.7910/DVN/9LS7OO

Author contribution

LN, ODS and OM: conceptualisation, laboratory experiments, formal analysis, software development. ODS, OM, CC: formal analysis. All authors participated in writing the original draft.

Competing

No competing interests.

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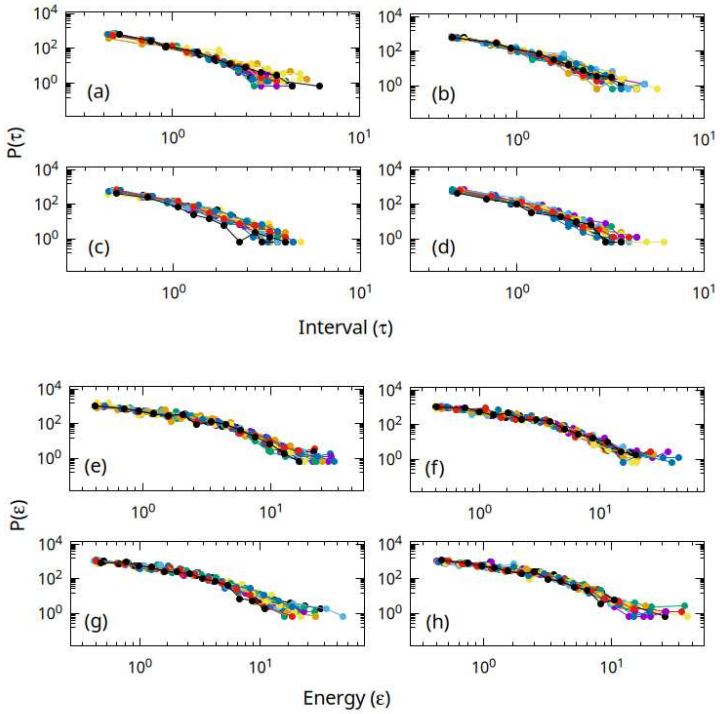


Figure 5: Log-log binned plots showing the scaling patterns of the probability distributions of the inter-event interval length $P(\tau)$ in [a–d] and energy pulse width $P(\epsilon)$ in [e–h]. (a) 15 treatments of type A (air) with an average power law exponent $< b_\tau >= -2.738$ (b) 15 AP treatments with $< b_\tau >= -2.753$ (c) 15 APH treatments with $< b_\tau >= -2.688$ (d) 15 APHE treatments with $< b_\tau >= -2.745$ (e) 15 A (air) treatments with an average energy pulse power law exponent $< b_\epsilon >= -2.167$ (f) 15 AP treatments with $< b_\epsilon >= -2.140$ (g) 15 APH treatments with $< b_\epsilon >= -2.160$ (h) 15 APHE treatments with $< b_\epsilon >= -2.144$. All exponent values estimated with MLE. Notice that the slight bending of the curves is due to finite effects.