F1000Research

Check for updates

RESEARCH ARTICLE

REVISED **EEG correlation at a distance: A re-analysis of two studies using a machine learning approach** [version 2; peer review: 2 approved]

Marco Bilucaglia [ID]1, Luciano Pederzoli2, William Giroldini2, Elena Prati2, Patrizio Tressoldi [ID]3

1Behavior and Brain Lab, Università IULM, Milano, Italy
2EvanLab, EvanLab, Firenze, Italy
3Science of Consciousness Research Group, Dipartimento di Psicologia Generale, Università degli Studi di Padova, Padova, 35131, Italy

Abstract

Background: In this paper, data from two studies relative to the relationship between the electroencephalogram (EEG) activities of two isolated and physically separated subjects were re-analyzed using machine-learning algorithms.
The first dataset comprises the data of 25 pairs of participants where one member of each pair was stimulated with a visual and an auditory 500 Hz signals of 1 second duration.
The second dataset consisted of the data of 20 pairs of participants where one member of each pair received visual and auditory stimulation lasting 1 second duration with on-off modulation at 10, 12, and 14 Hz.
Methods and Results: Applying a 'linear discriminant classifier' to the first dataset, it was possible to correctly classify 50.74% of the EEG activity of non-stimulated participants, correlated to the remote sensorial stimulation of the distant partner.
In the second dataset, the percentage of correctly classified EEG activity in the non-stimulated partners was 51.17%, 50.45% and 51.91%, respectively, for the 10, 12, and 14 Hz stimulations, with respect the condition of no stimulation in the distant partner.
Conclusions: The analysis of EEG activity using machine-learning algorithms has produced advances in the study of the connection between the EEG activities of the stimulated partner and the isolated distant partner, opening new insight into the possibility to devise practical application for non-conventional "mental telecommunications" between physically and sensorially separated participants.

Keywords

EEG, correlation at distance, machine learning, linear discrimination analysis.

Open Peer Review

Reviewer Status ✓ ✓

	Invited Reviewers	
	1	**2**
REVISED **version 2** published 29 Mar 2019	✓ report	✓ report
	⬆	⬆
version 1 published 10 Jan 2019	✗ report	? report

1 **Arnaud Delorme**, Paul Sabatier University, Toulouse, France

2 **Schubert R. Carvalho**, Vale Institute of Technology (ITV), Belém, Brazil

Any reports and responses or comments on the article can be found at the end of the article.

Corresponding author: Patrizio Tressoldi (patrizio.tressoldi@unipd.it)

Introduction

The test of whether or not the brain activities of two people who are only linked mentally – and with absolutely no other form of conventional communication – are correlated is a small research field that has existed for about 50 years (see Table S1 in (Giroldini *et al.*, 2016).

Despite accumulating evidence in favor of this correlation, this phenomenon is still considered controversial because of the proposed theories to explain it, no single theory is widely accepted. This correlation excludes the possibility of it originating from information received via the sense organs, from any direct link, even internet connections (e.g. (Jiang *et al.*, 2018; Lee *et al.*, 2017)) or from the electroencephalogram (EEG) activity of the stimulated partner of the pair, given their physical distance and isolation from each other.

We are left with postulating a type of quantum-like connection based on the distant mental connection between each partner (Galli Carminati *et al.*, 2017; Walach & Römer 2011; Walach *et al.*, 2016), even if this connection operates on a neurophysiological level.

The most commonly used method in this field of research is that of isolating the two partners, ensuring that there is no chance of sensorially obtaining information in the usual way, and the synchronous parallel recording of their respective neurophysiological activities. Therefore, one partner is stimulated at non-regular intervals with visual and/or auditory stimuli which can be structured, e.g. images, or non-structured, such as arrangements of black and white squares, or short duration sounds at a specific frequency. The choice to present the stimulations at irregular intervals, possibly also randomly, is important because it reduces neurophysiological autoactivation due to the expectation of stimulation.

At the end of the stimulation stage, each partner's recorded neurophysiological parameters are compared. If the non-stimulated partner's neurophysiological output shows activity that is simultaneous with the activity in the stimulated partner, and this activity is statistically greater than during the non-stimulated periods, we can confirm that it derives from a mental connection, or at least from a means that is different from conventional electromagnetic transmission.

Regarding the type of correlation between the partners' neural activities, a further step with respect to simply proving its existence is determining whether it is aspecific or specific; this means whether the type of observed activity – for example in the activity of the partner receiving specific sensorial stimulations, such as a visual stimulation with an on-off modulation at 10 Hz and 14 Hz – is also seen in the mentally connected partner, or if the activation is undifferentiated, for example at 10 Hz.

As would be expected, in the correlated activities of the two partners, the neurophysiological activity of the non-stimulated partner is always smaller, and it could be that classical analysis methods are unable to separate the activity signal from the background.

Beginning in the last few years, thanks to the development of artificial intelligence algorithms, different machine-learning algorithms have been applied to the analysis of EEG data (Chai *et al.*, 2017; de Carvalho *et al.*, 2017; Lotte *et al.*, 2007; Stober *et al.*, 2016). Among their many advantages is the possibility of simultaneously analyzing many variables that can be associated with a given event in both a linear and non-linear way, revealing coactivity configurations that would otherwise be difficult to see with other techniques. For an introduction to this type of algorithms see (Lantz, 2015).

In this study we re-analysed, using machine-learning techniques, the data of two studies aiming to more precisely identify the neurophysiological parameters of the EEG activity of non-stimulated partners correlated to those produced by their partners given specific sensorial stimulations.

The first dataset was obtained from the study of (Giroldini *et al.*, 2016). In this study, conducted using 25 pairs of participants, the stimulated partner was given a series of 128 visual and auditory stimulations of 1 second duration at 500 Hz, separated by random intervals of non-stimulation lasting from 4 to 6 seconds. Each partner's EEG activity was simultaneously recorded using 14-channel equipment.

The second dataset was obtained testing 20 pairs of participants, by (Giroldini *et al.*, 2018). In this study the stimulated partner was given random sequences of 32 visual and auditory stimulations of 1 second duration modulated at 10, 12, or 14 Hz, while the EEG activities of each partner were simultaneously recorded.

Methods
First dataset

Participants. Six Italian Caucasian healthy adults were chosen for the experiment, comprised of five men and one woman, with an average age of 35.5 years (SD = 8.3).

They were selected from the members of EvanLab, the private laboratory involved in this study. The criteria for their voluntary inclusion were their mutual friendship (> 10 years), and

their experience in being able to maintain prolonged focused concentration, a product of their familiarity with meditation and other practices requiring control of mental activities.

All together they contributed 25 different pairs of data.

The data were collected over three non-consecutive days. The dataset (available from: http://dx.doi.org/10.6084/m9.figshare.1466876 (Tressoldi, 2016)) includes details of pairings and the EEG data from a 14 EEG channels system.

Statement of ethics. The use of experimental subjects is in accordance with ethical guidelines as outlined in the Declaration of Helsinki, and the study has been approved by the Ethical Committee of the University of Padova's Department of General Psychology (prot. n. 63, 2012). Before taking part in the experiment, each subject gave his/her informed consent in writing after having read a description of the experiment.

Procedure. Each stimulated subject received 128 audio-visual stimulations (AVS). The auditory stimulus was composed of a 500 Hz sinusoid applied through 32 Ohm Parrot ZIK® earphones at a volume of about 80 dB. The visual stimulation was from high intensity red LEDs in a 4×4 arrangement placed approximately one meter from the subject being stimulated. The subject kept his/her eyes closed because the light could easily be detected through the eyelids.

Additionally, for each subject (no matter whether stimulated or not) 128 "surrogated" stimuli were drawn (nAVS). Their onsets were placed exactly 3s before the AVS onsets in order to be discriminated from the nAVS by our classification algorithm.

All preprocessing steps were done in Matlab using the EEGLab toolbox (Delorme & Makeig, 2004).

After filtering with a zero-phase FIR band-pass filter (2~40Hz), an ICA (Independent Component Analysis) was performed using a SOBI algorithm that, according to a previous study (Urigüen & Garcia-Zapirain, 2015), exhibits the best performance in the detection of the artifacts.

ICs (Independent Components) corresponding to artifacts were automatically identified and rejected using the MARA algorithm (Winkler *et al.*, 2011) that is based on a set of spatial, temporal and statistical features. Finally, a CAR (Common Average Reference) was performed.

Given that the type of stimulation produced a P300-like wave, we followed the common procedures used with Brain Computer Interfaces based on P300 (Hoffmann *et al.*, 2008). Data were first epoched with length of a 1s after the stimulus onset, then a sixth order Butterworth bandpass filter (1 ~ 12Hz) was applied and downsampled to 32Hz. Epoch lengths were thus lowered to 64 samples located at time points:

$$\{t_k\}_{k=1}^{64} = \{0s, -0.6667s, \ldots, +1.2333s, +1.2667s\}.$$

Samples were then amplitude-scaled according to the maximum and the minimum value inside each epoch, according to the equation:

$$x_{scaled} = \frac{x - \dfrac{(x_{max} + x_{min})}{2}}{\dfrac{(x_{max} - x_{min})}{2}}$$

Finally, scaled samples were concatenated to form a feature vector *v*, with a dimensionality of 65 × 14=910:

$$v = \left[x_1(t_1), x_1(t_2), \ldots, x_1(t_{64}), \ldots x_k(t_j), \ldots x_{14}(t_1), x_{14}(t_2), \ldots x_{14}(t_{64}) \right]$$

where $x_k(t_j)$ is the sample at time point t_j from channel *k*.

Feature selection. Reduction of the feature dimensionality is crucial to improve classification performances. A simple method for feature selection is based on the ranking of the Biserial Correlation Coefficients (Müller *et al.*, 2004). Considering a two-class dataset *D* (with just one numerical feature), the Biserial Correlation Coefficient r^2 for the feature is defined as:

$$r^2 = \left(\frac{\sqrt{N_A \cdot N_B}}{N_A + N_B} \frac{m(D_A) - m(D_B)}{s(D)} \right)$$

where D_A, D_B are the subsets of the dataset *D* composed by instances that belong to class *A*, *B*. *m*(.) and *s*(.) are, respectively, the sample mean and standard deviation operators. r^2 score is a measure of the "discriminative power" of the feature, reflecting how much of its "variance" is "explained" by the class affiliation.

After summing the coefficients of each feature and sorting the scores in descendent order, we selected the features of which the added score came to 95% of the total score.

For each stimulated and non-stimulated group of participants, the scalp distributions of r^2 coefficients (expressed as percentage, normalized to the total score) were drawn. Since each channel is associated with at most 65 features (as well as 65 r^2 coefficients), coefficients (one coefficient for each channel) are calculated as mean value.

Classification. As a classifier, we chose a Linear Discriminant (LD) classifier and the estimation of the classification accuracy was performed 10 times (to compensate the random variability of the estimated accuracy) by a 10-fold stratified cross-validation scheme.

We choose LD because, according to the literature (Lotte *et al.*, 2007), it has a very low computational requirement, is simple to use and generally provides good results (i.e. robustness to overfitting).

Since the feature selection is performed using information from the class labels, in order to avoid the overfitting and to train the classifier in a "fair way", feature selection was performed at each step within the cross-validation.

In addition to the LD classifier, at each step we classify our data using a Random classifier (which gets a prediction uniformly

distributed between the classes) that serves as a "baseline" to evaluate the LD classifier performance. The random classification is simply obtained randomly assigning (with uniform probability p=1/n) to each instance of the test, one of the class {C_1,C_2,…,C_n }, where n is the number of classes to be predicted.

At each cross-validation step, we calculated the mean accuracy and, finally, we calculated the mean and standard deviation of these mean accuracies.

The syntax in Matlab code is available here: https://doi.org/10.6084/m9.figshare.5132647.v6 (Tressoldi *et al.*, 2018)

Second dataset

The dataset is composed of 14 channels EEG data obtained from 20 pairs of participants (available from: https://doi.org/10.6084/m9.figshare.5132647.v6 (Tressoldi *et al.*, 2018)).

Participants. Five adults, two women and three men with an average age of 38.3 years (SD = 7.5), took part in this study. The selection criteria were their experience in mind control techniques (mainly meditation) and their mutual friendship, which we consider as essential pre-requisites for an adequate "mental and emotional connection" between the pairs. Each participant took turns in being both the stimulated partner and the non-stimulated partner with each of the others, making a total of 20 pair combinations.

Statement of ethics. The use of experimental subjects is in accordance with ethical guidelines as outlined in the Declaration of Helsinki, and the study has been approved by the Ethical Committee of the University of Padova's Department of General Psychology (prot. n. 63, 2012). Before taking part in the experiment, each subject gave his/her informed consent in writing after having read a description of the experiment

This sample size of 20 pairs of participants was estimated by setting the following parameters: statistical power = .80, a one-tailed Type I error = .05 and an expected effect size d = .5 for a one sample t-test (difference from a constant = 0: http://powerandsamplesize.com/Calculators/Test-l-Mean/1-Sample-1-Sided).

Stimuli. Visual stimuli consisted of red light flashes at 10, 12, 14 Hz (32 stimuli for each frequency) lasting 1 s with a minimum inter-stimulus interval of 4 s, while audio stimuli consisted of a 900 Hz sine tone, modulated on-off at the flashing frequencies.

The audio modulation was performed on a 900 Hz sinusoidal carrier and applied through 32 ohm impedance earphones at a volume of about 80 dB.

The interval between the three blocks was randomly varied at between 40 and 90 seconds.

The visual stimuli were provided by an array of 16 red LEDs positioned about 30 cm from the stimulated partner's closed eyes.

The three frequency blocks were presented randomly without repetition of the same frequency.

Additionally, for each subject (regardless of whether stimulated or not) the onsets of 32 "surrogated" stimuli (0 Hz, labelled as 255) were drawn from random positions of the entire recording: the first and the last 10 s were discarded, maintaining the same minimum inter-stimulus distance.

Preprocessing. All pre-processing steps were done as for the first dataset. Data were epoched with a 2s window after each stimulus onset. From each epoch and from channel, the PSD (Power Spectral Density) was estimated with a Welch's periodogram (1s long Hamming window with 50% of overlap) and spectral bins were normalized to the maximum value of the PSD.

Following the feature extraction procedure normally used with Brain-Computer-Interfaces systems based on SSVEP (Müller-Putz *et al.*, 2005), we concatenated spectral bins corresponding to both stimulus frequencies and their first harmonics: F = {10, 20; 12, 24; 14, 28} Hz.

The feature vector v, with a dimensionality of $6 \times 14 = 84$, is thus defined as:

$$v = [p_1(10), p_1(20), \dots, p_k(f_j), \dots, p_{14}(14), p_{14}(28)]$$

where p_k (f) is the spectral power at frequency $f_j \in F$ from channel k.

Feature selection. The 4-class (10, 12, 14, 0) prediction problem was decomposed in 6 different 2-class prediction problems, creating 6 different datasets containing all the possible couples of the 4 classes: {10, 12}, {10, 14}, {10, 0}, {12, 14}, {12, 0} and {14, 0}.

Feature selection was based on the ranking of the Biserial Correlation Coefficients as with the first dataset.

Classification. As with the first dataset, we used a Linear Discriminant (LD) classifier compared with a Random classifier. Again, we performed a 10-fold stratified cross-validation scheme, with feature selection inside each cross-validation step.

Experimental hypotheses

For both datasets and in the stimulated and non-stimulated partners, we expected a higher level of correct classification of the EEG activity correlated with the visual and auditory stimulations with respect to the EEG activity correlated with the periods of non-stimulation, corresponding to the inter-stimulus intervals.

However, whereas for the stimulated partners, it is expected a great difference between these two EEG activities, we expected a much small difference, even if statistically significant, in the non-stimulated partners, given that none sensorial stimulation can be transferred from the stimulated to the non-stimulated partners.

Results
First dataset

Figure 1 and Figure 2 show the scalp distributions of r^2 coefficients (expressed as percentage, normalized to the total score),
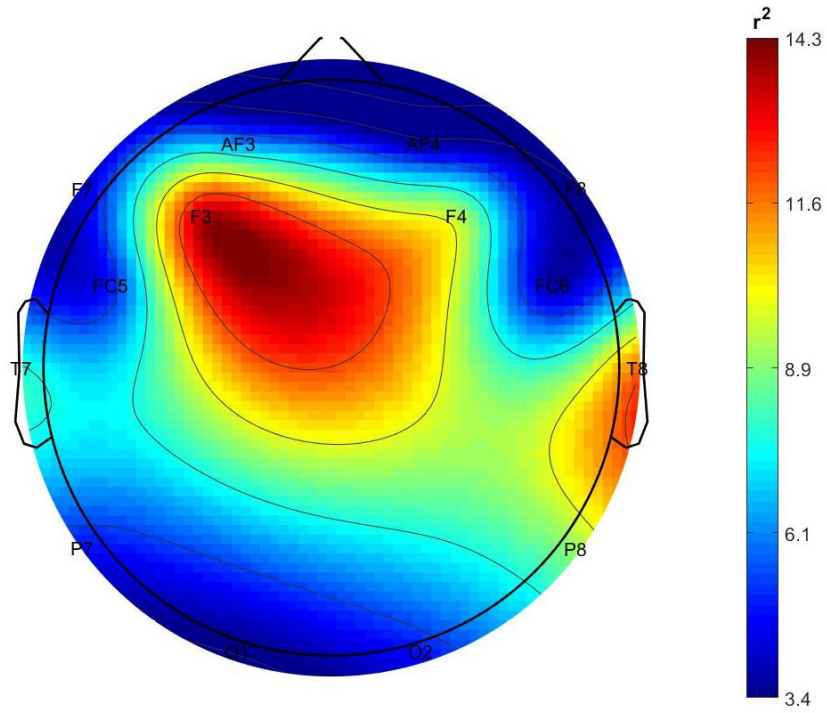
Figure 1. Topographic distribution of r^2 coefficients (stimulation vs non-stimulation discriminative power) in the stimulated participants.
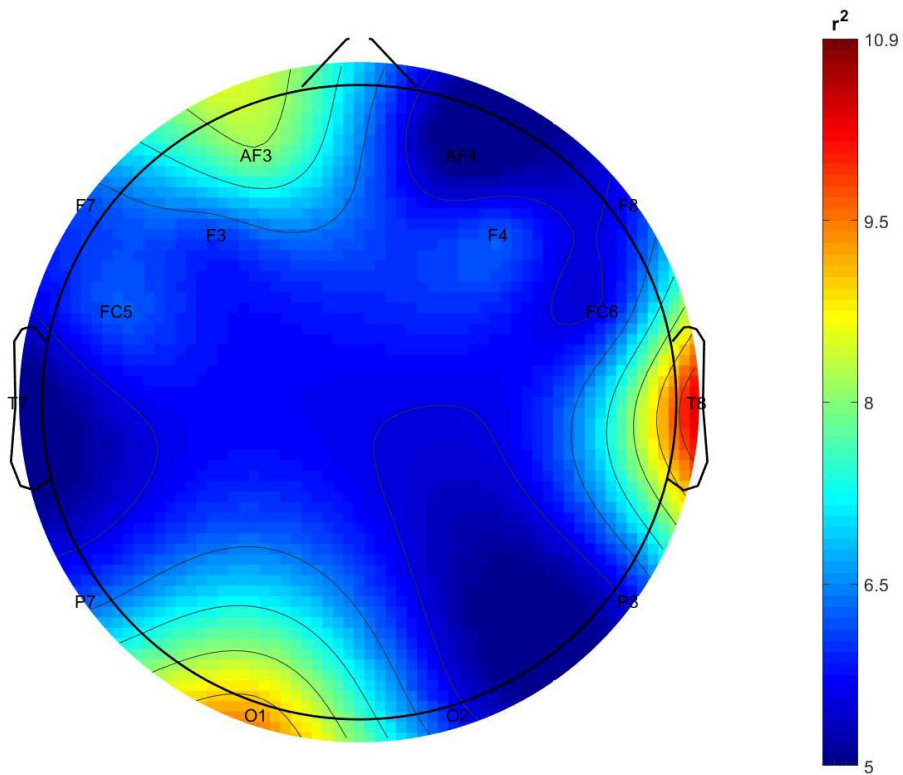

Figure 2. Topographic distribution of r^2 coefficients (stimulation vs non-stimulation discriminative power) in the non-stimulated participants.

representing the discriminative power between the periods of stimulation and no-stimulation (interstimulus intervals) of the features, for the stimulated and not-stimulated participants, respectively.

As it is shown in Figure 1, the class-discrimination (AVS vs nAVS) in the stimulated participants derives mostly from central and left frontal and right temporal electrodes, while in the non-stimulated participants their class is best discriminated by features from the right temporal and left occipital electrodes.

The percentages of the classification accuracy are reported in Table 1 and Table 2 for the stimulated and the non-stimulated participants, respectively.

Inferential statistics and parameters estimation. For the inferential statistics, we chose the comparison of percentage of correct discrimination between the stimulation and non-stimulation conditions, comparing each with the percentage obtained with the Random Classifier using a one-tailed paired t-test and a comparison using the Bayes Factor calculation using the default Cauchy prior value of .707. As a parameter estimation,

we chose the measurement of Cohen's effect size d and the relative confidence interval of 95%, all one-directional. All statistical analyses were conducted using Jasp software (Jasp Team, 2018).

Results are presented in Table 3 below, while data from the Bayes Factor Robustness Check are shown in the Extended data.

Comment. While results for the stimulated partners are as expected, those observed from non-stimulated partners, from a statistical point of view indicate the presence of an EEG signal corresponding to the stimulation periods, even if the percentage of correct classification is not particularly high. Furthermore, the origins of these differences (see Figure 2) correspond to channels T8 and O1, which correspond to brain areas involved in processing auditory and visual information respectively.

Second dataset

Figure 3 and Figure 4 show the scalp distributions of the mean r^2 coefficients (expressed as percentage, normalized to the total score), representing the discriminative power between the periods

Table 1. Percentages of the classifications for the stimulated participants. LD: linear discriminant classifier; Random: random classifier.

	LD	Random
Iteration #1	82.76	49.84
Iteration #2	82.95	50.58
Iteration #3	82.98	49.33
Iteration #4	82.78	49.64
Iteration #5	82.72	51.42
Iteration #6	82.58	49.91
Iteration #7	83.09	50.62
Iteration #8	82.86	51.10
Iteration #9	82.68	50.30
Iteration #10	83.00	50.34
Mean	82.84	50.31
SD	0.16	0.65

Table 2. Results of the classifications for the non-stimulated participants.

	LD	Random
Iteration #1	51.32	49.33
Iteration #2	51.09	49.81
Iteration #3	49.81	49.78
Iteration #4	51.06	48.96
Iteration #5	51.09	50.16
Iteration #6	50.33	50.95
Iteration #7	50.42	50.64
Iteration #8	50.95	49.72
Iteration #9	50.97	51.29
Iteration #10	50.34	50.30
Mean	50.74	50.09
SD	0.48	0.72

Table 3. Inferential statistics and parameters estimation of the comparison of the percentage of correct classification of the periods of stimulation and non-stimulation between the linear discriminant and the random classifier.

	Stimulated participants	Non-stimulated participants
t-test (*p*-value)	154.84 (<.001)	2.06 (.035)
Cohen's *d* (lower 95% CI)	48.9 (28.6)	.65 (.06)
Bayes Factor $_{H1/H0}$	2.32^{e13}	2.63

Figure 3. Topographic distribution of *r*² coefficients (stimulation vs non-stimulation discriminative power) of the stimulated participants. Top left: 14 Hz vs 0 Hz; top centre: 12 Hz vs 0 Hz; top right: 12 Hz vs 14 Hz; bottom left: 10 Hz vs 0 Hz; bottom centre: 10 Hz vs 14 Hz; bottom right; 10 Hz vs 12 Hz.
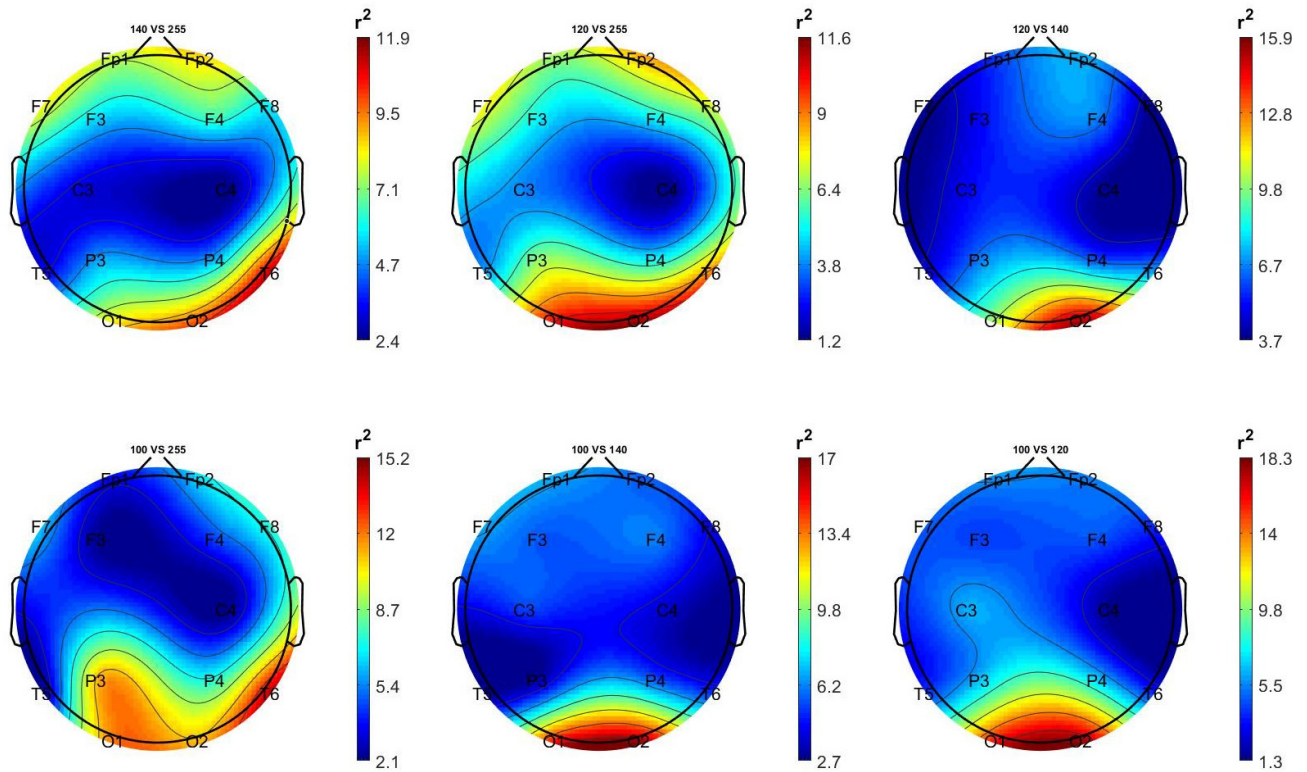

Figure 4. Topographic distribution of coefficients of *r*² (stimulation vs non-stimulation discriminative power) the non-stimulated participants. Top left: 14 Hz vs 0 Hz; top centre: 12 Hz vs 0 Hz; top right: 12 Hz vs 14 Hz; bottom left: 10 Hz vs 0 Hz; bottom centre: 10 Hz vs 14 Hz; bottom right; 10 Hz vs 12 Hz.
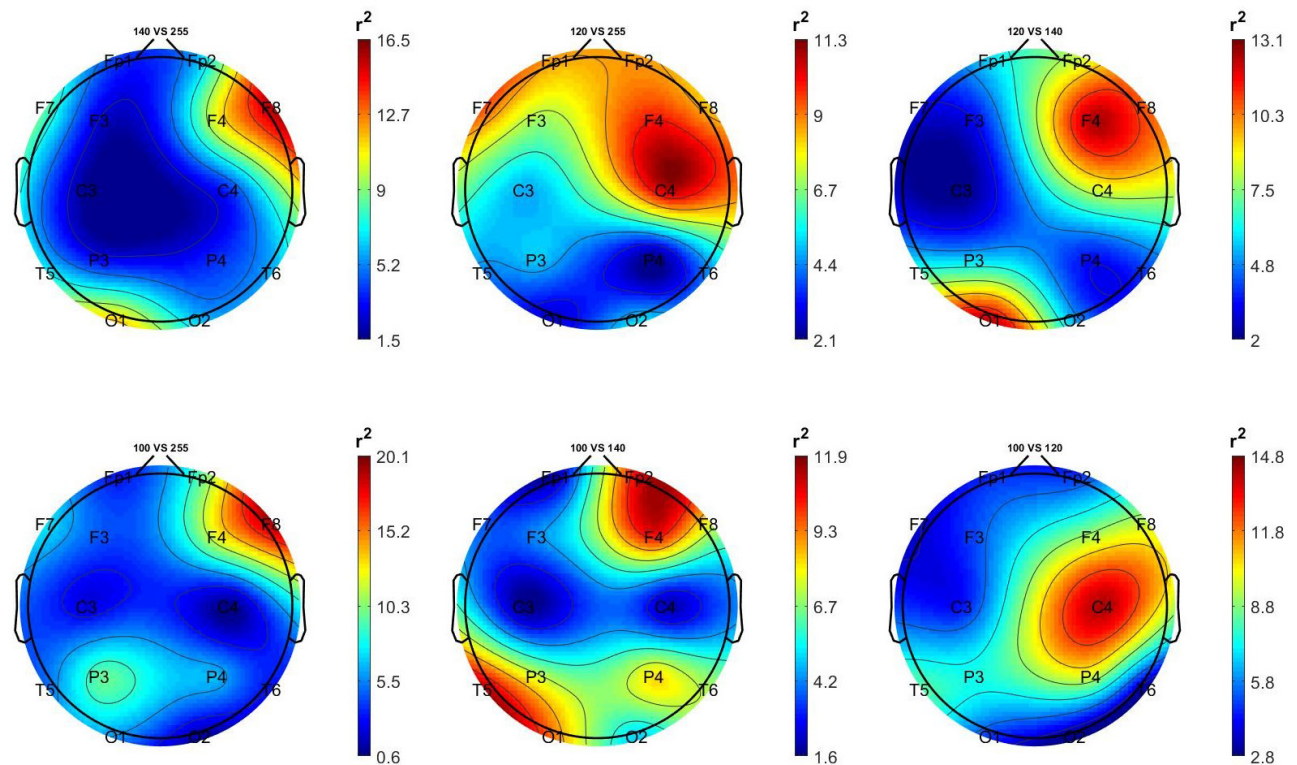
of stimulation and no-stimulation (interstimulus intervals) of the features, for each 2-class problem for each group (stimulated and non-stimulated pairs).

Comment. As shown in Figure 3, in the stimulated participants the EEG activity generated by the three frequencies of stimulation is best distinguished from the 0 Hz class (non-stimulation) by the right occipital and temporal regions' features.

In the non-stimulated participants (Figure 4), the 10 Hz and 14 Hz are best distinguished from the 0 Hz class by frontal and frontocentral regions features.

Percentages of classification accuracy. The percentages of correct classification for each comparison for each of the 10 cross-validation iterations and their descriptive statistics observed in the stimulated participants are presented in Table 4.

Inferential statistics and parameters estimation. Similarly to the first dataset, for the inferential statistics we chose the comparison with the percentage of LD classifier discrimination between the three stimulation conditions at 10 Hz, 12 Hz, and

14 Hz, and the non-stimulation (0 Hz), comparing each with the percentages obtained from the Random Classifier using a paired one-tailed t-test and a comparison by way of the Bayes Factor calculation using the default Cauchy prior value of .707. As a parameter estimate, we chose Cohen's d and the relative confidence interval of 95%, all one-directional. These results are presented in Table 5, while the Bayes Factor Robustness Check data are shown in the Extended data.

Comment. As seen from the means, the percentage of correct classification of EEG activity between the non-stimulation and stimulation periods with the three frequency values is always greater than 70%, as confirmed by the inferential statistics results.

The percentages of correct classification of each comparison for each of the 10 cross-validation interactions and their descriptive statistics observed in the non-stimulated participants are presented in Table 6.

Inferential statistics and parameters estimation. Results of inferential statistics and parameter estimates are shown in Table 7.

Table 4. Percentages of classification accuracies between the periods of stimulation and non-stimulation for the stimulated participants.

	10Hz vs 0Hz		12Hz vs 0Hz		14Hz vs 0Hz	
	LD	**Random**	**LD**	**Random**	**LD**	**Random**
Iteration#1	70.39	50.47	71.95	50.70	72.27	50.23
Iteration#2	71.25	49.30	72.50	47.66	72.42	49.38
Iteration#3	70.55	50.00	71.64	50.39	72.27	50.63
Iteration#4	69.84	49.45	73.05	51.56	71.72	50.31
Iteration#5	69.22	51.41	72.73	51.33	71.48	48.36
Iteration#6	69.84	50.31	73.05	51.88	71.72	50.94
Iteration#7	70.70	50.00	72.34	48.52	72.19	53.05
Iteration#8	70.08	48.91	72.03	48.83	72.11	50.63
Iteration#9	69.61	49.69	72.34	50.55	72.58	50.23
Iteration#10	69.61	50.16	72.19	51.41	72.11	52.42
Mean	**70.11**	49.97	**72.38**	50.28	**72.09**	50.62
SD	0.61	0.69	0.46	1.38	0.34	1.34

Table 5. Inferential statistics and parameters estimation of the comparison of the percentage of correct classification of the periods of stimulation and non-stimulation between the linear discriminant and the random classifier in the stimulated participants.

LD	Random	t-test	p	d	95%CI-Inf	BF_{10}
10 Hz vs 0	10 Hz vs 0 r	56.95	< .001	18.01	10.92	$7.45e^9$
12 Hz vs 0	12 Hz vs 0 r	51.32	< .001	16.23	9.84	$3.26e^9$
14 Hz vs 0	14 Hz vs 0 r	51.91	< .001	16.42	9.95	$3.57e^9$

Table 6. Percentages of classification accuracies between the periods of stimulation and non-stimulation for the non-stimulated participants.

	10Hz vs 0Hz		12Hz vs 0Hz		14Hz vs 0Hz	
	LD	**Random**	**LD**	**Random**	**LD**	**Random**
Iteration#1	51.33	49.45	52.19	47.66	52.11	50.94
Iteration#2	50.78	50.47	50.16	48.83	51.64	50.31
Iteration#3	51.41	49.53	50.16	51.09	52.73	48.91
Iteration#4	52.27	48.67	51.56	49.84	53.44	48.75
Iteration#5	52.97	49.45	50.39	52.19	50.78	46.80
Iteration#6	50.47	50.39	49.69	47.58	50.16	51.09
Iteration#7	50.39	49.77	50.55	49.30	51.56	47.97
Iteration#8	52.42	52.50	48.52	50.08	52.42	49.14
Iteration#9	50.63	49.84	50.08	51.33	53.52	50.47
Iteration#10	49.06	50.47	51.25	51.09	50.78	48.28
Mean	**51.17**	50.05	**50.45**	49.90	**51.91**	49.27
SD	1.15	1.02	1.02	1.56	1.14	1.4

Table 7. Inferential statistics and parameters estimation of the comparison of the percentage of correct classification of the periods of stimulation and non-stimulation between the linear discriminant and the random classifier in the non-stimulated participants.

LD	Random	t-test	p	d	95%CI-Inf	$BF_{H1/H0}$
10 Hz vs 0	10 Hz vs 0r	2.21	0.027	0.70	0.09	3.19
12 Hz vs 0	12 Hz vs 0r	0.87	0.202	0.27	-0.26	0.66
14 Hz vs 0	14 Hz vs 0r	4.97	< .001	1.57	0.75	101.98

Comment. The most interesting result is that the activity related to two of the three stimulation frequencies, 10 Hz and 14 Hz, is classified above 50% with respect to the non-stimulation periods, even if in a more evident way for 14Hz. The fact that there are no differences between the 12Hz and the non-stimulation condition suggests that the base rhythm in non-stimulated participants is predominantly at 12Hz. Moreover, since the direct comparison between the activity corresponding to 10Hz and 14Hz, does not show differences with respect to the random condition (Mean = 50.2; SD = .75; Mean = 50.3; SD = 1.79), it suggests that in the non-stimulated participants, the EEG activity corresponding to these two frequencies either above or below 12Hz.

Discussion

The machine-learning re-analyses of data from two studies relative to the distant correlation between EEG activity of participant pairs who were sensorially stimulated and participants who were connected to them only mentally, not only confirmed the existence of a correlation, as shown in the two studies from which they were taken, but also pointed out the degree of classification between stimulated and non-stimulated periods.

In the first dataset, the stimulation of EEG activity with luminous and auditory stimuli at 500Hz produced a slight perturbation also in that of the non-stimulated partners which allowed to distinguish it from the non-stimulation periods with a modest 50.74%. Even if the statistical comparison with the random classifier, slightly support a difference between the periods of the distant stimulation with respect to the period of distant non-stimulation, a difference of only 0.74%, cannot be considered very reliable.

In the second dataset, however, stimulation with frequencies of 10Hz and 14Hz, allowed to better distinguish this type of related perturbation, with percentages of 51.17% and 51.91% respectively, while for 12Hz stimulation, the discrimination was similar to the random classifier one.

Could these last results depend on a generic increase of alpha activity due to an increase relaxation or tiredness of non-stimulated participants during the task? We rule out this explanation because we observed differences with respect to the non-stimulation periods only for the 10 and 14 Hz, more pronounced for the last one (see percentage of classification, effect size and Bayes Factor values).

Even though, with hindsight, the choice to use frequencies that are within or close to the Alpha activity was not optimal, given that this was the dominant EEG activity in non-stimulated participants, the evidence that these are distinguishable even in the EEG activity of non-stimulated participants opens interesting possibilities, should this research path be continued in terms of practical applications.

Information regarding the potential neural sources of these signals obtained from this study must also be validated with confirmatory studies and also with more sophisticated equipment than those used by us.

From a theoretical point of view, while we can safely reject the theory that the observed activity in non-stimulated participants is due to a traditional sensorial transmission (albeit weak) from the stimulated participants' EEG activity, we as yet do not have enough information to determine if this correlation – which does not necessarily involve transmission – has quantum-like properties like the physical particles studied in quantum mechanics. Indeed, to determine this it would, first of all, entail closing a series of loopholes, as was done in quantum mechanics to reject the theory that distant connection used the laws of classical physics (Giustina *et al.*, 2015; Shalm *et al.*, 2015). For example, the loophole showing the impossibility of communication at the speed of light between participant pairs would need closing.

Pending a better understanding of the laws regulating the correlation between the EEG activity of two mentally-connected participants, we believe that data obtained so far in this field, including that of other researchers, clearly show that if classification algorithms of signals down to the level of single participants are perfected, along with an online instead of the offline classification, the road towards practical use of mental telecommunication can be opened, even if for now it is based on binary symbolic codes.

Mental telecommunication, not just those based on electromagnetic waves but also those of the future based on quantum technologies, have the advantage of not requiring repeaters or security measures and would certainly be beneficial from an economical point of view.

Data availability

Underlying data
First dataset: Figshare: EEG correlates of social interaction at distance, http://dx.doi.org/10.6084/m9.figshare.1466876 (Tressoldi, 2016).

Second dataset: Figshare: Brain-to-Brain interaction at a distance: a global or differential relationship? https://doi.org/10.6084/m9.figshare.5132647.v7 (Tressoldi *et al.*, 2018)

Data are available under the terms of the Creative Commons Attribution 4.0 International license (CC-BY 4.0).

Extended data
Dataset 1: Stimulated participants. Bayes Factor Robustness Check; Non-stimulated participants: Bayes Factor Robustness Check

Dataset 2: Non-stimulated participants. Bayes Factor Robustness Check: 10 Hz vs 0 Hz; Bayes Factor Robustness Check: 14 Hz vs 0 Hz

Both datasets are available on Figshare: Brain-to-Brain interaction at a distance: a global or differential relationship? https://doi.org/10.6084/m9.figshare.5132647.v7 (Tressoldi *et al.*, 2018)

Data are available under the terms of the Creative Commons Attribution 4.0 International license (CC-BY 4.0).

Grant information
The author(s) declared that no grants were involved in supporting this work.

References

Chai R, Ling SH, San PP, *et al.*: **Improving EEG-Based Driver Fatigue Classification Using Sparse-Deep Belief Networks.** *Front Neurosci.* 2017; **11**: 103.
PubMed Abstract | **Publisher Full Text** | **Free Full Text**

de Carvalho SR, Filho IC, de Resende DC, *et al.*: **A Novel Procedure for Classification of Early Human Actions from EEG Signals.** In *2017 Brazilian Conference on Intelligent Systems (BRACIS)*. IEEE. 2017; 240–245.
Publisher Full Text

Delorme A, Makeig S: **EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis.** *J Neurosci Methods.* 2004; **134**(1): 9–21.
PubMed Abstract | **Publisher Full Text**

Galli Carminati G, Martin F, Carminati F: **A Very Simple Quantum Model of Mind and Matter.** *NeuroQuantology.* 2017; **15**(2).
Publisher Full Text

Giroldini W, Pederzoli L, Bilucaglia M, *et al.*: **EEG correlates of social interaction at distance [version 5; referees: 2 approved].** *F1000Res.* 2016; **4**: 457.
Publisher Full Text

Giroldini W, Pederzoli L, Bilucaglia M, *et al.*: **Exploring the Brain-to-Brain interaction at a distance: a global or differential relationship?** 2018.
Publisher Full Text

Giustina M, Versteegh MA, Wengerowsky S, *et al.*: **Significant-Loophole-Free Test of Bell's Theorem with Entangled Photons.** *Phys Rev Lett.* 2015; **115**(25): 250401.
PubMed Abstract | **Publisher Full Text**

Hoffmann U, Vesin JM, Ebrahimi T, *et al.*: **An efficient P300-based brain-computer interface for disabled subjects.** *J Neurosci Methods.* 2008; **167**(1): 115–125.
PubMed Abstract | **Publisher Full Text**

JASP Team: **JASP (Version 0.9.2.0) [Computer software].** 2018.
Reference Source

Jiang L, Stocco A, Losey DM, *et al.*: **BrainNet: A Multi-Person Brain-to-Brain Interface for Direct Collaboration Between Brains.** *ArXiv.* 2018.
Reference Source

Lantz B: **Machine learning with R: discover how to build machine learning algorithms, prepare data, and dig deep into data prediction techniques with R.**

Packt Publishing. 2015.
Reference Source

Lee W, Kim S, Kim B, *et al.*: **Non-invasive transmission of sensorimotor information in humans using an EEG/focused ultrasound brain-to-brain interface.** *PLoS One.* 2017; **12**(6): e0178476.
PubMed Abstract | **Publisher Full Text** | **Free Full Text**

Lotte F, Congedo M, Lécuyer A, *et al.*: **A review of classification algorithms for EEG-based brain-computer interfaces.** *J Neural Eng.* 2007; **4**(2): R1–R13.
PubMed Abstract | **Publisher Full Text**

Müller KR, Krauledat M, Dornhege G, *et al.*: **Machine learning techniques for brain-computer interfaces.** *Biomed Tech.* 2004; **49**(1): 11–22.
Publisher Full Text

Müller-Putz GR, Scherer R, Brauneis C, *et al.*: **Steady-state visual evoked potential (SSVEP)-based communication: impact of harmonic frequency components.** *J Neural Eng.* 2005; **2**(4): 123–130.
PubMed Abstract | **Publisher Full Text**

Shalm LK, Meyer-Scott E, Christensen BG, *et al.*: **Strong Loophole-Free Test of Local Realism.** *Phys Rev Lett.* 2015; **115**(25): 250402.
PubMed Abstract | **Publisher Full Text** | **Free Full Text**

Stober S, Sternin A, Owen AM, *et al.*: **Deep Feature Learning for EEG Recordings.** *ArXiv.* 2016.
Reference Source

Tressoldi P: **EEG correlates of social interaction at distance.** *figshare.* Fileset. 2016.
http://www.doi.org/10.6084/m9.figshare.1466876.v8

Tressoldi P, Pederzoli L, Bilucaglia M, *et al.*: **Brain-to-Brain interaction at a distance: a global or differential relationship?** *figshare.* Fileset. 2018.
http://www.doi.org/10.6084/m9.figshare.5132647.v7

Urigüen JA, Garcia-Zapirain B: **EEG artifact removal-state-of-the-art and guidelines.** *J Neural Eng.* 2015; **12**(3): 031001.
PubMed Abstract | **Publisher Full Text**

Walach H, Römer H: **Generalized Entanglement - A Nonreductive Option for a Phenomenologically Dualist and Ontologically Monist View of Consciousness.** In *Studies in Neuroscience, Consciousness and Spirituality.* Berlin, Heidelberg: Springer Science Business Media. 2011; 81–95.
Publisher Full Text

Walach H, Tressoldi P, Pederzoli L: **Mental, behavioural and physiological nonlocal correlations within the Generalized Quantum Theory framework.** *Axiomathes.* 2016; **26**(3): 313–328.
Publisher Full Text

Winkler I, Haufe S, Tangermann M: **Automatic classification of artifactual ICA-components for artifact removal in EEG signals.** *Behav Brain Funct.* 2011; **7**(1): 30.
PubMed Abstract | **Publisher Full Text** | **Free Full Text**

Open Peer Review

Current Peer Review Status: ✔ ✔

- -

Version 2

Reviewer Report 27 August 2019

https://doi.org/10.5256/f1000research.20515.r46491

✔ **Schubert R. Carvalho**

Vale Institute of Technology (ITV), Belém, Brazil

The paper is scientifically sound, and the authors made improvements from the first submission and adequated handle my raised concerns of the first submission.

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Machine Learning, Deep Learning, Brain-Computer Interface

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard.

Reviewer Report 30 April 2019

https://doi.org/10.5256/f1000research.20515.r46492

✔ **Arnaud Delorme**

 Brain and Cognition Research Centre, CNRS, Paul Sabatier University, Toulouse, France

In experiment 2, the experimenters didn't mix randomly the three frequencies (they were presented in blocks). However, the order of the blocks was different in the different subjects, so this mitigates my original comment of the absence of randomization.

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: EEG processing

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard.

Version 1

Reviewer Report 21 March 2019

https://doi.org/10.5256/f1000research.19259.r42948

? **Schubert R. Carvalho**
Vale Institute of Technology (ITV), Belém, Brazil

The study presented in this paper is challenging and can be fascinating; it aims to verify whether or not two participants are only connected mentally without using sensory organs. To check this connection, the authors decided to use a machine learning approach. They used a linear classifier and framed the problem as a classification task. The methodology was validated on two public datasets that both used EEG signals as a measure for brain activity.
The methodology is simple to grasp and understand. The main steps of the methodology can be reproduced. However, it seems the authors get lost in the results section.

The study design can be improved to verify mental telecommunication (whether or not two brains are connected). Figures 1 and 2 show the stimulated and non-stimulated brains of the participants. One good comparison, was showing the differences between the brains at rest. If the goal is to verify if two brains are connected, one observation that is missing is the brain at rest vs. brain at stimulus for both groups. For example, if the two brains (two groups) are connected, then the classification between both should be random.
The results shown in table 1 and 2 sound obvious. Table 1 shows the accuracy of the stimulated and non-stimulated brain (stimulated participants group), the classes show different patterns of activity, as measured by the high classification accuracy compared to the data of table 2. However, the comparison that is missing is between the data of the stimulated and non-stimulated subjects during the stimulation period. So, if the classification accuracy is at random, it suggests a brain connection. Mental telecommunication is the primary goal of this paper after all.

The same principle of analysis was done for dataset 2 (Results section: Second dataset). It is not possible to conclude mental telecommunication from this analysis, as shown in table 4. So, one interesting experiment that could be done to verify mental telecommunication would be to analyze the non-stimulated group data before and during the stimulation, to see if the mental states are separable as in the stimulated group. If this analysis is in the paper, it is not clear.

In the second paragraph of the discussion section, the authors argue that a modest classification accuracy of 50.74% allowed to distinguish it from the non-stimulation condition. From a machine learning point of view, this is considered a random classification. Moreover, this study (as it is in the moment) did not show evidence (machine learning results) for mental telecommunication — the same for the third

paragraph (second dataset).

Is the work clearly and accurately presented and does it cite the current literature?
Partly

Is the study design appropriate and is the work technically sound?
Partly

Are sufficient details of methods and analysis provided to allow replication by others?
Partly

If applicable, is the statistical analysis and its interpretation appropriate?
Not applicable

Are all the source data underlying the results available to ensure full reproducibility?
Yes

Are the conclusions drawn adequately supported by the results?
No

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Machine Learning, Deep Learning, Brain-Computer Interface

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard, however I have significant reservations, as outlined above.

> Author Response 25 Mar 2019
> **Patrizio Tressoldi**, Università degli Studi di Padova, Padova, Italy
>
> "The study design can be improved to verify mental telecommunication (whether or not two brains are connected). Figures 1 and 2 show the stimulated and non-stimulated brains of the participants. One good comparison, was showing the differences between the brains at rest. If the goal is to verify if two brains are connected, one observation that is missing is the brain at rest vs. brain at stimulus for both groups. For example, if the two brains (two groups) are connected, then the classification between both should be random."
>
> **Reply: what Figures 1 and 2 show, is precisely the spatial distribution of the features (extracted with the method described in the "Features selection" section) ranked by their discriminative power (r2 coefficients) for the stimulation versus the non-stimulation periods, in the stimulated (Figure 1) and the non-stimulated participants (Figure 2).**
> **The same information is presented in the Figures 3 and 4 with respect to the second dataset.**
> **We now have clarified this in the Figures' captions.**
>
> "The results shown in table 1 and 2 sound obvious. Table 1 shows the accuracy of the stimulated

and non-stimulated brain (stimulated participants group), the classes show different patterns of activity, as measured by the high classification accuracy compared to the data of table 2. However, the comparison that is missing is between the data of the stimulated and non-stimulated subjects during the stimulation period. So, if the classification accuracy is at random, it suggests a brain connection. Mental telecommunication is the primary goal of this paper after all."

Reply: your suggestion that a random classification accuracy comparing the data of the stimulated and non-stimulated subjects during the stimulation period, should be the critical proof of a "brain-to-brain" connection at distance should be valid postulating a similar EEG activity in the stimulated and non-stimulated subjects.
In the new paragraph "Experimental hypotheses" on page 5, we now have clarified that this effect is not possible because there cannot be a transmission or connection of the "physical" characteristics of the EEG activity trigger by the visual-auditory stimulations, between the stimulated and non-stimulated subjects, but only a still undefined type of information which weakly affect the EEG activity of the non-stimulated subjects.

"The same principle of analysis was done for dataset 2 (Results section: Second dataset). It is not possible to conclude mental telecommunication from this analysis, as shown in table 4. So, one interesting experiment that could be done to verify mental telecommunication would be to analyze the non-stimulated group data before and during the stimulation, to see if the mental states are separable as in the stimulated group. If this analysis is in the paper, it is not clear."

Reply: we now have clarified that the data and the statistics reported in Tables are precisely those related to the comparison between the periods of stimulation and the interstimulus (no-stimulation) periods.

"In the second paragraph of the discussion section, the authors argue that a modest classification accuracy of 50.74% allowed to distinguish it from the non-stimulation condition. From a machine learning point of view, this is considered a random classification. Moreover, this study (as it is in the moment) did not show evidence (machine learning results) for mental telecommunication — the same for the third paragraph (second dataset)."

Reply: we agree that the marginal 0.74% difference, even if statistically different from the random classification, cannot be considered reliable (now added in the discussion). However, the differences observed in the second dataset, even if very modest according to the standards used in the machine learning community, it is sufficient to support the hypothesis that the EEG activity of the non-stimulated participants is in some way related to those of the stimulated one. As commented in the "Discussion" section, we think that this hypothesis can be further supported improving our machine learning algorithms. This is our optimistic opinion of course.

Competing Interests: No competing interests were disclosed.

Reviewer Report 30 January 2019

Arnaud Delorme
 Brain and Cognition Research Centre, CNRS, Paul Sabatier University, Toulouse, France

This article intends to show that machine learning methods might be able to pick on subtle EEG activity and perform classification above chance level and show true EEG correlation at a distance. The article is well written and clear.

I was able to download the data and reproduce the results of experiment 2. I am not sure about the first experiment as the processing script for that experiment seems to be missing. The data processing, machine learning and cross-validation scheme seemed straightforward and appropriate. It is still possible that by trying many machine learning approaches, one could obtain positive results just by chance. This should be mentioned in the discussion as a potential limitation.

The most interesting result is that participants who are not exposed to stimuli nevertheless have a response to them that the classifier can pick up above chance expectations. One important caveat I have seen in the experimental design of experiment 2 is that the stimuli are not randomly intermixed. Instead there is a sequence of one stimulus type and then another one, etc. As subjects perform the experiment, their EEG changes (for example they might get tired as the experiment progresses which could affect their alpha brain waves). So one might have more alpha for one stimulus type simply because a given stimulus type is presented first. The classifier can then pick up on that. The sequence of stimuli should have been randomized for that reason. In other words, since stimuli of a given type are grouped, the classifier might simply pick up on the fact that some epochs belong to the beginning of the experiments, and some others belong to the end.

If my assessment is correct, I would remove the second experiment from the manuscript. Once I get the processing script for the first experiment, I would be able to assess potential pitfalls.

Abstract: the abstract should mention statistical results.

Is the work clearly and accurately presented and does it cite the current literature?
Yes

Is the study design appropriate and is the work technically sound?
Partly

Are sufficient details of methods and analysis provided to allow replication by others?
Yes

If applicable, is the statistical analysis and its interpretation appropriate?
Partly

Are all the source data underlying the results available to ensure full reproducibility?
Yes

Are the conclusions drawn adequately supported by the results?
Partly

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: EEG processing

I confirm that I have read this submission and believe that I have an appropriate level of expertise to state that I do not consider it to be of an acceptable scientific standard, for reasons outlined above.

Author Response 30 Jan 2019

Patrizio Tressoldi, Università degli Studi di Padova, Padova, Italy

Sorry for missing the syntax for reproducing our machine learning analyses on the first dataset. We have just uploaded it "MachineLearningSyntaxExperiment1" on
https://doi.org/10.6084/m9.figshare.5132647.v8
We are also pleased you were able to reproduce our analyses on the dataset 2 and appreciated their appropriateness.

As to your main concerns that the results observed in the participants who were not exposed to stimuli, were due to "alpha activity of one stimulus type simply because a given stimulus type is presented first and they might get tired as the experiment progresses which could affect their alpha brain waves", we consider this interpretation disputable given the following reasons:

1. The stimulus types (10, 12, 14 Hz) were presented randomly. How is it possible to obtain a fair good level of correct classification of all three stimulus types with respect to the non-stimulation periods in the stimulated participants and in two out of three stimulus types in the non-stimulated participants? Let us suppose an almost equal distribution of the initial presentation of the three stimulus types among the 20 pairs of participants, how is it possible to discriminate their corresponding EEG activity with respect to the non-stimulation one if based on just the type of the first stimulus?

2. In the non-stimulated participants we observed differences with respect to the non-stimulation periods only for the 10 and 14 Hz, more pronounced for the last one (see percentage of classification, effect size and Bayes Factor values). How is it possible to justify these differences postulating a common tiring effect?

Competing Interests: No competing interests were disclosed.

The benefits of publishing with F1000Research:

- Your article is published within days, with no editorial bias

- You can publish traditional articles, null/negative results, case reports, data notes and more

- The peer review process is transparent and collaborative

- Your article is indexed in PubMed after passing peer review

- Dedicated customer support at every stage

For pre-submission enquiries, contact research@f1000.com

F1000Research