BCI-Walls: A robust methodology to predict success or failure in brain computer interfaces

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Abstract

Brain computer interfaces (BCI) require realtime detection of conscious EEG changes so that a user can for example control a video game. However scalp recordings are contaminated with noise, in particular muscle activity and eye movement artefacts. This noise is non-stationary because subjects will voluntarily or involuntarily use their facial muscles or move their eyes. If such non-stationary noise is powerful enough a detector will no longer be able to distinguish between signal and noise which is called SNR-wall. As a relevant and instructional example for BCI we have recorded scalp signals from the central electrode Cz during 8 different activities ranging from relaxed, over playing a video game to reading out loud. We then filtered the raw signals using four different postprocessing scenarios which are popular in the BCI-literature. The results show that filtering with a 1st order highpass makes it impossible to detect conscious EEG changes during any of the physical activities. A wideband bandpass filter between 8-18 Hz allows the detection of conscious EEG changes while playing a phone app, Sudoku, word search and colouring. Reducing the bandwidth during postprocessing to 8-12 Hz allows additionally conscious detection of EEG during reading out loud. The SNR-wall applied to BCI gives now a hard and measurable criterion to determine if a BCI experiment can detect conscious EEG changes or not. It enables one to flag up experimental setups and postprocessing scenarios where misinterpreting of scalp recordings is highly likely, in particular misinterpreting non-stationary muscle activity as conscious EEG changes.

Introduction

Brain computer interfaces (BCI) have broadly the task to turn brain activity (EEG) into actions, for example to move a character in a video game or a wheelchair. In the simplest way this is achieved by testing if the EEG signal has reached a certain threshold or has gone below one [1]. However, it is well known that muscle activity (EMG) from facial and neck muscles contaminate the EEG [2] and that the spectra of EEG and EMG overlap, in particular above 20 Hz. Various techniques have been devised to separate the EEG content from the EMG one. By far the most popular approach is principle component analysis (PCA) or independent component analysis (ICA) but these are not realtime algorithms and thus not possible to be used in BCI which operates in closed loop with the user. For realtime applications such as BCI one needs to resort to direct causal filtering techniques using bandpass filters, the short
time Fourier Transform, wavelet transform \cite{3,5} or applying a chain of derivatives \cite{6}. All these approaches are inferior to the offline noise removal techniques such as ICA or PCA.

Given the limited effectiveness of noise reduction techniques, measurements will be substantially contaminated by EMG because of the overlap in EEG and EMG frequencies, no matter what kind of pre-processing has been applied. The standard solution to remove noise is averaging which can be achieved in both the time domain and frequency domain.

- **Time-domain:** In the “evoked potential” (ep) paradigm the EEG is averaged stimulus locked which assumes that EMG noise is uncorrelated to the stimulus repetition and averages out.

  \[
  \text{ep}[m] = \frac{1}{N} \sum_{n=0}^{N} d[m + n \cdot N]
  \]

  where \( N \) is the number stimulus repetitions and their responses registered as \( d[m + n \cdot N] \). The more repeated stimuli \( N \) are presented the more the EMG noise is reduced. For example in a P300 speller a subject looks at a flashing “A” and the EEG is then added to the average over and over again until a threshold has been reached. The more repetitions of the letter “A” the better the signal to noise ratio but the longer the time to bring it over a threshold to decide the user has looked at the flashing “A”.

- **Frequency-domain:** Here, the idea is that the subject can consciously reduce (or sometimes increase) the power of a narrow frequency band. To detect this change the signal is analysed in the frequency domain. If the band-power of a frequency band reaches a certain threshold then an action can be triggered for example moving a cursor. Again, averaging takes place because the Fourier Transform or a bank of bandpass filters accumulate the correlation between sine/cosine-waves \( e^{-j2\pi kn/N} \) with chunks of EEG \( d[n] \):

  \[
  X[k] = \sum_{n=0}^{N-1} d[n] \cdot e^{-j2\pi kn/N} \quad k = 0, 1, 2, \ldots, N - 1
  \]

  where \( N \) is the number of samples the averaging takes place, \( d[n] \) is the EEG and \( X[k] \) the resulting spectrum. If the chunk of EEG is long then the frequency spectrum will deliver clear peaks in the band of interest and thresholding becomes more and more reliable.

No matter if the detection process is performed in the time- or frequency-domain one needs to wait for \( N \) samples until a decision can be made so that a signal reaches a threshold. Fig.\[A\] shows such a case where a cartoon signal is shown where a signal has to reach the threshold \( \gamma \) which then can be used to control for example a cursor in a BCI game. The threshold \( \gamma_0 \) is chosen in a way that the noise with noise variance \( \sigma_0^2 \) does not reach the threshold but the desired conscious EEG signal does (indicated with the tick symbol).

While in classical detection theory there is always a number of samples \( N \), if averaged over these, reliable detection is possible. However, this does not take into account non-stationary noise which is the case when recording EEG contaminated with EMG (Fig.\[B\]). Here, the noise variance changes, for example, from the small noise variance \( \sigma_0^2 \) to a large noise variance \( \sigma_1^2 \) and then back to the small noise variance \( \sigma_0^2 \). The three peaks indicated with “X” are noise peaks. The threshold \( \gamma_1 \) could be set higher than \( \sigma_0^2 \) so that the 2nd and 3rd noise peaks are not detected.
Fig 1. Effects of stationary versus non-stationary noise on signal detection. A) Signal detection with stationary noise, B) signal detection with non-stationary noise

However, now we are encountering a problem at “?” which could also be noise or signal. It is most likely an actual signal as the noise variance has just dropped again to a lower level but this is only because we know. One could argue as above that averaging over more samples \( N \) will eventually average out the noise but because of the changing noise variance peaks as the “?” become ambiguous and can either be signal or noise. Analytically this means that with non-stationary noise the number of samples \( N \) required to detect robustly a signal can reach infinity (\( N \to \infty \)) and thus detection is not possible at all. This limitation is called SNR-wall [7]. EMG is certainly a non-stationary noise source – in particular in everyday situations when subjects walk, play a video game or simply talk. This means that every activity a subject does will define a hard SNR-wall because the EMG is non-stationary. If the SNR is below the SNR-wall it is no possible to detect the EEG at all and thus it is not possible at all to design a BCI system for that activity.

In this paper we introduce the concept of SNR-walls to EEG measurement to have an objective way to determine if an experiment can detect EEG in principle in the presence of non-stationary noise. As an instructional example how to generally calculate SNR-walls we have recorded the EEG from subjects during a range of different tasks. We then calculated the SNR-walls for the different activities to gauge if it’s possible to construct a BCI system given the non-stationary noise created by these tasks.

**Methods**

**SNR-walls**

In this section we briefly explain the relevant theory of SNR-walls and how to calculate them practically. Tandra et al [7] provide a detailed derivation of the theory while here we focus on those aspects which apply to our BCI paradigm, namely detecting a conscious increase of EEG power in a specified frequency band.

Let us consider a signal measured with an electrode \( \tilde{d}[n] \) placed on the head of a subject:

\[
\tilde{d}[n] = \tilde{a}[n] + \tilde{b}[n] + \tilde{c}[n] \tag{3}
\]

where \( \tilde{c}[n] \) is the consciously controlled part of the EEG. \( \tilde{b}[n] \) is the background EEG activity which the subject cannot control. \( \tilde{a}[n] \) are all artefacts such as muscle activity added to the measurement. Important for this paper is that the noise \( \tilde{a}[n] \) is non-stationary: for example when smiling the power of \( \tilde{a}[n] \) will be larger and when relaxing the power of \( \tilde{a}[n] \) will be less. This needs to be kept in mind as this property...
will be crucial later when calculating the SNR-wall. Together \( \tilde{b}[n] \) and \( \tilde{a}[n] \) form the noise \( \tilde{r}[n] \) of the signal measured. Generally the raw EEG signal from the electrode requires filtering, which is at least DC and powerline interference removal but usually also bandpass filtering if only a certain EEG band is of interest:

\[
d[n] = (\tilde{r}[n] + \tilde{c}[n]) * f[n]
\]

where from now on signals without the \( \tilde{\cdot} \) are the ones after filtering.

The decision problem can be considered as a binary hypothesis testing problem which can be written as:

\[
H_0 : d[n] = r[n] + 0
\]

\[
H_1 : d[n] = r[n] + c[n]
\]

The hypothesis \( H_0 \) represents the situation where the signal at the electrode contains just noise and \( H_1 \) where consciously generated EEG is present.

Central to the BCI system is that it is able to detect the conscious EEG \( c[n] \) so that an action can be generated, for example steering a wheelchair. Thus, we need a detector which takes the signal \( d[n] \) and decides with a threshold \( \gamma \) if it has just been noise or consciously generated EEG on top of the noise.

If one knows nothing about signal except that it will increase or decrease one can just detect the average power over \( N \) samples and gains a test statistic:

\[
T(X) = \frac{1}{N} \sum_{n=1}^{N} x[n]^2
\]

where the average power over \( N \) samples creates a random variable \( T \) which is then compared against a threshold \( \gamma \) which decides if the signal has contained the consciously controlled EEG component \( c[n] \) or not.

Let us first assume that our total noise/artefacts \( r[n] = a[n] + b[n] \) have a single nominal variance \( \sigma_r^2 \) so that we can calculate our detection probabilities \( P(D) \):

\[
P(D)|H_0 \sim \mathcal{N} \left( 0 + \sigma_r^2, \frac{1}{N} 2(0 + \sigma_r^2)^2 \right)
\]

\[
P(D)|H_1 \sim \mathcal{N} \left( T(c) + \sigma_r^2, \frac{1}{N} 2(T(c) + \sigma_r^2)^2 \right)
\]

where \( c \) is the consciously controlled EEG power.

The SNR of the signal \( d(n) \) can be expressed as:

\[
\text{SNR} = \frac{T(c)}{\sigma_r^2}
\]

where \( T(c) \) is the average EEG power of the consciously generated EEG component \( c[n] \) and \( \sigma_r^2 \) is our nominal noise variance (i.e. noise power).

The probability of a false alarm \( P_{FA} \) can be written as:

\[
P_{FA} = Q \left( \frac{\gamma - \sigma_r^2}{\sqrt{\frac{2}{N} \sigma_r^2}} \right)
\]

where \( N \) is the number of samples, \( \sigma_r^2 \) the noise power, and \( \gamma \) the detection threshold.

In a similar way the probability for detection \( P_D \), it is given by

\[
P_D = Q \left( \frac{\gamma - (T(c) + \sigma_r^2)}{\sqrt{\frac{2}{N} (T(c) + \sigma_r^2)}} \right)
\]
By eliminating $\gamma$ in Eq. 11 and Eq. 12 and with the help of Eq. 7 and Eq. 10 we are able to obtain an equation for the number of samples $N$ required to detect robustly the conscious EEG component $c$:

$$N = \frac{2[Q^{-1}(P_{FA}) - Q^{-1}(P_D)(1 + SNR)]^2}{SNR^2}$$

which means that with a constant $\sigma_r$ one just needs to average the power over $N$ timesteps (Eq. 7) to obtain a robust detection and with sufficiently large $N$ it is always possible to perform a robust detection. However, we need to remind us that $r'[n] = a[n] + b[n]$ is non-stationary and that the corresponding variance of the noise $\sigma_r$ is non-stationary.

In particular the artefact part $a[n]$ is non-stationary, for example when a person suddenly smiles or speaks with changing EMG activity which is even the case for pure mental tasks [8]. To capture the noise uncertainty we define the parameter $\rho$ which is the ratio between the largest noise variance $\sigma_{r, \text{max}}^2$ over the smallest one $\sigma_{r, \text{min}}^2$:

$$\rho = \sqrt{\frac{\sigma_{r, \text{max}}^2}{\sigma_{r, \text{min}}^2}}$$

Our nominal variance $\sigma_r^2$ of the signal is then defined as:

$$\sigma_{r, \text{min}}^2 = \frac{1}{\rho} \sigma_r^2$$

$$\sigma_{r, \text{max}}^2 = \rho \sigma_r^2$$

and can be determined together with $\sigma_{r, \text{min}}$ and $\sigma_{r, \text{max}}$.

Having defined the noise uncertainty we can express our false alarm and detection probabilities as a function of $\rho$:

$$P_{FA} = Q \left( \frac{\gamma - \rho \sigma_r^2}{\sqrt{\frac{2}{N} \rho \sigma_r^2}} \right)$$

$$P_D = Q \left( \frac{\gamma - \left( T(c) + \frac{1}{\rho} \sigma_r^2 \right)}{\sqrt{\frac{2}{N} \left( T(c) + \frac{1}{\rho} \sigma_r^2 \right)}} \right)$$

In a low SNR environment, $SNR + 1 \approx 1$ can be assumed and Eqs. 17, 18 and 7 combined yield:

$$N = \frac{2 \left[ Q^{-1}(P_{FA}) - Q^{-1}(P_D)(1 + SNR) \right]^2}{\left[ SNR - \left( \rho - \frac{1}{\rho} \right) \right]^2}$$

where $N$ is again the number of samples that are needed to achieve the target probability of a permitted false alarm and probability of detection. However now we see that if the SNR becomes lower than the integration steps $N$ not only increase but become infinite when the SNR is less than $\rho - \frac{1}{\rho}$. This critical SNR is called SNR wall. Since only the denominator of Eq. 19 counts, the SNR wall can be calculated simply by:

$$SNR_{\text{wall}} = \rho - \frac{1}{\rho}$$

The SNR-wall represents a fundamental limitation of detection performance, which means that relevant uncertainties cannot be countered by a longer sensing time. In
order to determine if EEG can be detected or not we need to determine both the noise uncertainty $\rho$ and the SNR of our measured brain signal.

Having now derived the underlying analytics we can devise a step by step guide how to determine if EEG changes $c[n]$ can be detected at all:

1. Calculate the SNR-wall (Eq. [20]) by evaluating the minimum noise variance $\sigma^2_{r,\text{min}}$ and the maximum noise variance $\sigma^2_{r,\text{max}}$ of the brain recording.

2. Determine the signal to noise ratio $\text{SNR}$ of the brain recording (Eq. [10]).

3. Check if the $\text{SNR}$ is larger than the SNR-wall. If this is the case then it is possible to detect the conscious EEG change:

$$\text{conscious EEG changes } c[n] \text{ detectable} = \begin{cases} \text{yes} & \text{SNR} > \text{SNR}_{\text{wall}} \\ \text{no} & \text{otherwise} \end{cases} \quad (21)$$

In the following sections we call the entire three step process of determining if conscious EEG can be detected “BCI-Wall”.

Data acquisition

Data was obtained from 20 healthy participants (9 males, 11 females). Prior to the experiment, participants were given an information sheet and were asked to give signed consent by signing 2 consent forms, one for the researchers and another for them to keep. Ethical approval was given by the ethics committee at the Institute of Neuroscience and Psychology, School of Psychology at the University of Glasgow, with reference 300210055. The data was acquired using an Attys data acquisition device (www.attys.tech), and its data acquisition programmes ‘attys-ep’ and ‘attys-scope’. The Attys is made up of 2 channels and a 24-bit ADC. A compound electrode allowed connection of the Cz to both channels. The difference in potential of both sides of the brain were measured between Cz and A1 (left side), connecting the negative input of Channel 2 (also acting as ground) to the left ear, and between Cz and A2 (right side) connected to the negative input of Channel 1, while the participants’ facial expressions were recorded for later observation.

Due to issues with the equipment, participants 2 and 6 had to be excluded from the study. About 180 sets of data are analysed in this study. These are stored in an open-access database [9], all ethics files can also be found on the database.

Data was recorded during 10 activities, including a VEP and a P300, where a stimulus was produced randomly after 7 to 13 seconds. The tasks ranged in mental activity and were VEP and P300 recordings, jaw clenching, reading, colouring, attempting a word search, trying a Sudoku, playing ‘Subway Surfers’ game on the phone, lying with eyes closed and repeat with eyes opened. Subjects sat in front of the camera to do this experiment and all tasks were recorded.

EEG pre-processing

The raw EEG data $\tilde{d}[n]$ will always undergo causal filtering prior to detection. Here, we have subsumed the pre-processing in the filter function $f[n]$ which itself consists of a chain of filters. We are presenting four different conditions which reflect popular use cases in the literature.

A Wideband energy detector with minimal filtering: $f[n] = \text{DC-removal, 50 Hz powerline bandstop}$ which will create max EMG interference and also low frequency fluctuations. This is hardly used in the literature but acts here as a
worst case scenario as the whole EMG spectrum is allowed to interfere with the detection.

B Differentiator: \( f[n] = \text{derivative/1st order highpass} \ (f[n] - f[n-1]) \). DC-removal, 50 Hz powerline bandstop which has been used for example in [6].

C Wideband bandpass: \( f[n] = 2\text{nd order Butterworth bandpass} \ 8-18 \text{ Hz}, \)
DC-removal, 50 Hz powerline bandstop with moderate rejection of higher EMG power used for motor imagination [10].

D Narrow bandpass: \( f[n] = 2\text{nd order Butterworth bandpass} \ 8-12 \text{ Hz}, \)
DC-removal, 50 Hz powerline bandstop detecting alpha power around 10 Hz and rejects the higher frequency EMG power [11].

These 4 post-processing scenarios are applied separately to the data of all subjects and tasks, except for those with obvious broken electrode signals or strong artefacts.

**BCI-wall calculation**

As outlined above the BCI-wall calculations require three steps: 1) SNR calculation, 2) SNR-wall calculation and 3) comparing SNR and SNR-wall to determine if conscious EEG detection is possible. We are now describing how this can be done practically and is also an instructional example for other datasets.

**SNR**

Generally the SNR is calculated as a ratio between signal power and noise power (Eq. [10]). Measuring the pure EEG \( c \) and its power \( T(c) \) is only indirectly possible as it is not ethical to paralyse subjects. The P300 evoked potential offers an individual estimate of the consciously generated signal power \( T(c) \) calculated from the peak P300 voltage. This will be used for estimating the power of the signal for both a time domain task (i.e. P300) and frequency domain task (i.e. motor imagination):

- **Time-domain power of the signal:** The P300 peak can be used straight away for a time domain calculation of its power (Fig. [2]A):
  \[
  T_t(c) = c^2_{\text{max}}
  \]  
  where the \( T_t(c) \) is the power of the pure EEG in the time domain.

- **Frequency-domain power of the signal:** BCI systems using the frequency domain change the power of a narrow frequency band (Fig. [2]B), for example by motor imagination. Here, we assume that:
  - The EEG power generated in a narrow frequency band is comparable to the power generated in the time domain \( T_t(c) \). This is indicated between the panels Fig. [2]A and B by noting that the peak powers are identical.
  - However, because motor imagination reduces power consciously the actual conscious power \( T_f(c) \) is only as strong as the reduction of power. Here, we assume a 40% reduction of power.

Given that only the reduction is the conscious power change \( c \) and anything else will be absorbed in the noise term \( r \) we can calculate the pure signal power (in contrast to the noise) as:

\[
T_f(c) = T_t(c) - T_t(c) \cdot 40\%
\]  

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Fig 2. Flow diagram illustrating the calculation of the SNR and SNR-wall.
A) Time domain signal for the SNR calculation takes the power $T_t(c)$ of the P300 peak as the consciously generated EEG change. B) Frequency domain signal power for the SNR calculation takes the power $T_t(c)$ and assumes a conscious 40% reduction of the signal power in a narrow band around a peak. C) For the overall SNR the $\sigma_r^2$ is calculated over the whole EEG recording. To calculate the SNR-wall the maximum $\sigma_{r,\text{max}}^2$ variance and minimum $\sigma_{r,\text{min}}^2$ variance is detected with a sliding window sample by sample. If the SNR is greater than the SNR-wall then a conscious change in the EEG can be detected. If the SNR is less than the SNR-wall then it is impossible to detect a conscious change.

After having calculated the power of the signal $T_f(c)$ we now need to calculate the power of the noise. Given that the small P300 evoked potentials $c$ are buried in the EEG $d$, one can assume that the noise variance containing a consciously generated signal and without one are basically identical [12]: $\sigma_r^2 \approx \sigma_d^2$. Thus we take the variance of the EEG epoch $d[n]$ (Fig. 2D) as

$$\sigma_r^2 \approx T(d)$$

(24)

where power of the EEG epoch $T(d)$ is calculated with Eq. 7 which is the average power or variance.

SNR-Wall

In order to calculate the SNR-wall we need to first calculate the ratio between maximum and minimum noise power $\rho$ (Eq. 14) which in turn requires to find the minimum and maximum variance in chunks of size $\tau$ of the EEG. By calculating the $\rho(n)$ by sliding over the signal $d[n]$ sample by sample we create a $\rho$ which depends on the sample position $n$:

$$\rho_{\text{chunk}}[n] = T(d[n \ldots n + \tau])$$

(25)
which in turn will yield a maximum variance $\sigma^2_{r,\text{min}}$ within a chunk and a minimum variance $\sigma^2_{r,\text{max}}$ within another chunk (see Fig. 2):

$$\sigma^2_{r,\text{min}} = \min \rho_{\text{chunk}}[n] \quad (26)$$
$$\sigma^2_{r,\text{max}} = \max \rho_{\text{chunk}}[n] \quad (27)$$

With Eqs. (14) and (20) one can then calculate the SNR-wall.

**Comparing SNR and SNR-Wall: conscious control detection**

If the SNR of the EEG (Eq. 10) is above the SNR-wall (Eq. 20) then detection of the conscious EEG change $c$ is possible. Otherwise not.

For every task, for example “Sudoku”, there will be individual pairs of SNR and SNR-wall values from every subject. Because the SNR and SNR-wall values are calculated over all subjects they are random variables. A t-test is used to determine if the SNR for all subjects is significantly above the SNR-wall for each task and for each of the four post-processing scenarios.

**Results**

Fig. 3 shows the results of the SNR-walls and the SNRs for the different experimental conditions and different tasks. Both SNR and SNR-walls are shown in dB on a scale from -15 dB to +15 dB. The y-axis shows the results for each separate task so that one can decide if it is possible to detect a conscious change in the EEG reliably or not. Panel A) shows the results for the energy detector. Here, all SNR values are lower than the SNR-walls which means that a wideband detector cannot detect a conscious change of EEG at all. In B) pre-filtering is done by a simple 1st order highpass which is popular for realtime BCI [6]. Here, only when lying down with eyes open or closed it is possible to detect a conscious change. It is interesting to see that in particular the
tasks with high EMG content such as jaw clench, reading, colouring, word search and Sudoku have very similar SNR values. This is not surprising as a plain highpass filter cannot suppress EMG which is predominantly at higher frequencies. Predictably a bandpass filter from 8-18 Hz in C) yields significantly better results with now having SNR values above the SNR-walls for lying (eyes closed), using a phone app, playing Sudoku, doing word search and colouring. Reading which engages a large amount of facial muscles and the jaw clench as a worst case scenario obliterate any detection effort. It’s interesting to see that lying down with eyes closed won’t allow detection which anecdotally points to the subjects being more stressed and thus tense with their eyes closed. Best detection performance is achieved with a narrow low frequency bandpass around the alpha band of 10 Hz with all tasks but jaw clench allowing detection of a consciously changed EEG. Overall this shows that narrow bandpass filtering at lower frequencies is the preferred option. C) is a typical filtering approach for motor imagination and shows that detection is possible as long as no excessive facial muscle activity is generated. D) as the most robust approach requires the user to control their alpha band, for example by opening or closing their eyes and is the most robust approach.

Discussion

In this paper we have introduced an objective hard criterion which determines if it is possible to detect conscious signal in an EEG at all in a recording contaminated with non-stationary noise which we call BCI-wall. We then determined the BCI-wall for a range of different tasks with non-stationary noise while applying different filtering techniques to lower the BCI-wall. Overall the BCI-wall is highest if filtering is broadband and can be lowered by performing narrow band filtering in the lower EEG frequency band.

As outlined in the introduction, EEG is contaminated with different forms of noise where EMG is the hardest to remove because of its broad frequency spectrum ranging from 20 to 80 Hz. The gold standard to measure the EMG contribution is by neuromuscular blockade where a subject is temporally paralysed and, thus, generates zero EMG. Measuring brain activity from a paralysed subject reveals substantial EMG contamination over 20 Hz and matches our results where the SNR-wall is lowest if one uses a narrow bandpass around the 10 Hz alpha band well below 20 Hz. However, to our knowledge only one paralysis-study calculated the signal to noise ratio per frequency band which reports similar dB values in the region of 0dB to what we have obtained. Interestingly they also reported that the SNR ratio can be up to five fold (i.e. 17dB) higher for central electrodes using a Laplacian which would mean that the SNR were significantly above the SNR-wall. However, this is only the case for central electrodes and not frontally.

While EMG contamination has been widely acknowledged and being a problem which needs to be addressed it appears that most BCI studies and reviews stay silent about how they have dealt with EMG interference. The first comprehensive literature survey investigating artefact removal finds that most BCI papers do not report whether or not they have considered the presence of EMG (67.6%) or EOG (53.7%) artefacts in the brain signals. This situation has not improved much ten years later where 41% of the studies did not mention any artefact removal process of EEG and even where artefacts were mentioned 22% of those studies did not do any cleaning or artefact removal. Given the existence of a relevant SNR-wall under both laboratory and everyday conditions it should be imperative to take the relevant SNR-wall seriously to determine if EEG detection is possible at all given the experimental conditions.
SNR-wall theory was developed in the field of telecommunications where it is common that a multitude of transmitters create non-stationary background noise \cite{19,24} and thus making it with increasing number of transmitters impossible, for example, for a mobile phone to communicate with its base station. The SNR-wall calculations are able to make hard predictions if a telecommunications system will be able to work as intended or not. Similar rigorous assessments should also be introduced to BCI systems so that their success or failure can be predicted and that misinterpretation of scalp recordings can be avoided, in particular misinterpreting non-stationary EMG changes as conscious EEG changes.

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**Conflict of Interest Statement**

B.P. is CEO of Glasgow Neuro LTD which manufactures the Attys DAQ board. This does not alter our adherence to PLOS ONE policies on sharing data and materials.

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