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Research Paper

Transitioning EEG experiments away from the laboratory using a Raspberry Pi 2

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ABSTRACT

Background

Electroencephalography (EEG) experiments are typically performed in controlled laboratory settings to minimise noise and produce reliable measurements. These controlled conditions also reduce the applicability of the obtained results to more varied environments and may limit their relevance to everyday situations.

New method

Advances in computer portability may increase the mobility and applicability of EEG results while decreasing costs. In this experiment we show that stimulus presentation using a Raspberry Pi 2 computer provides a low cost, reliable alternative to a traditional desktop PC in the administration of EEG experimental tasks.

Results

Significant and reliable MMN and P3 activity, typical event-related potentials (ERPs) associated with an auditory oddball paradigm, were measured while experiments were administered using the Raspberry Pi 2. While latency differences in ERP triggering were observed between systems, these differences reduced power only marginally, likely due to the reduced processing power of the Raspberry Pi 2.

Comparison with existing method

An auditory oddball task administered using the Raspberry Pi 2 produced similar ERPs to those derived from a desktop PC in a laboratory setting. Despite temporal differences and slight increases in trials needed for similar statistical power, the Raspberry Pi 2 can be used to design and present auditory experiments comparable to a PC.

Results

Our results show that the Raspberry Pi 2 is a low cost alternative to the desktop PC when administering EEG experiments and, due to its small size and low power consumption, will enable mobile EEG experiments unconstrained by a traditional laboratory setting.

1. Introduction

Laboratory settings provide highly controlled environments ideal for sensitive measures and experimentation such as electroencephalography (EEG) recordings, which can otherwise be contaminated by background interference due to sound, muscle activity, and radio frequency waves (Van Hoey et al., 2000). Unfortunately these benefits are also coupled with certain drawbacks as results may not be entirely applicable to settings outside the laboratory. Alternative EEG designs allow for increased mobility but are often expensive, utilise fewer electrodes, or require the use of cumbersome equipment. A proposed solution to escaping the confines of the laboratory involves a Raspberry Pi 2 computer, a small, low-cost (~$35) device that has become popular among hobbyists and computer engineers but has also been utilised for research purposes. The Raspberry Pi device has been programmed to use a camera for real-time identification of individuals using palm vein patterns (Joardar et al., 2015), for comparison of protein sequences (Robson and Barker, 2015), analysis of light pulses used in non-invasive diffuse correlation spectroscopy (Tivnan et al., 2015), and is capable of intensive data analysis and data mining (John et al., 2015).

In traditional laboratory experiments a Macintosh or Windows PC running customisable software, such as E-Prime, Superlab, or Matlab with the Psychophysics toolbox, are used to present various stimuli. Such desktop computers are computationally powerful and can present a variety of highly controlled and accurate stimuli, but these systems come at both a monetary and mobility cost, weighing several kilograms and costing hundreds of dollars. While something more portable, such as a laptop or tablet can be used, the cost of EEG hardware is still significant. The Raspberry Pi 2 is a versatile solution to the issue of cost, mobility, and reliability when it comes to stimulus presentation. This device is inexpensive, lightweight (approximately 45 g), and highly versatile. The Raspberry Pi 2 offers several ways to connect external USB peripherals, displays, and auditory equipment, and it has 40 General Purpose Input/Output (GPIO) pins. Many of these pins can be programmed for use in various tasks such as flashing LEDs and controlling electric motors. The low power requirements allow the Raspberry Pi 2 to be powered by any 5 V, 1.2A power supply (such as 4 AA batteries in series) without generating a considerable amount of heat, allowing the device to run for long peri-

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ods depending on battery size and any connected peripherals. The Python programming language can be used to generate auditory and visual stimuli while software specific for cognitive psychological testing, such as OpenSesame (Mathôt et al., 2012), offers an intuitive method for experimental design. Through OpenSesame and Python it is possible to recreate a traditional auditory oddball task involving the presentation of common, standard tones and rare, target tones. Event related potentials (ERPs) that occur time-locked with the presentation of these tones can then be derived from collected EEG data.

This paper demonstrates that the Raspberry Pi 2 can be used to present stimuli for EEG experiments and recordings, allowing for more mobile psychological experiments. An auditory oddball-paradigm was presented using both the Raspberry Pi 2 and a traditional desktop PC while EEG data was recorded to an external laptop. The results demonstrate that similar temporal and spatial ERP activity is evoked by both computer systems.

2. Material and methods

2.1. Participants

A total of 10 members of the university community participated in the experiment (mean age = 21.10; age range = 18–25; 1 male). Each participant completed an identical session on both the Raspberry Pi 2 computer and a desktop PC computer with order being counterbalanced. Participants were all right-handed, and all had normal or corrected normal vision and no history of neurological problems. All participants gave informed consent, were compensated at a rate of $10/h for their time, and the experimental procedures were approved by the internal Research Ethics Board of the University of Alberta.

2.2. Materials & procedure

Participants completed an auditory oddball task to measure their P3 and MMN responses to task-relevant, target tones. A pair of Logitech Z130 speakers played one of two different tones (either 1500 or 1000 Hz; sampled at 44,100 Hz; two channel; 16-ms duration; 2-ms linear ramp up and down), with the rare target tone always at 1500 Hz. The volume of the sound output was kept constant for every participant. Speaker volume was increased for the Raspberry Pi 2 to match that of the desktop PC since the Raspberry Pi 2 was quieter compared to the desktop PC when the volume level of the speakers were matched. Participants were asked to sit still and fixate on a 1° white cross in the center of a black background that stayed constant throughout the auditory task. Whenever the rare tone was heard, participants were instructed to move only their right hand to press the spacebar on a keyboard placed in front of them.

Participants were seated 57-cm away from a 1920 × 1080 pixel ViewPixx/EEG LED monitor running at 120 Hz with simulated-backlight rastering. For the Rapsberry Pi 2, stimuli were presented using a Raspberry Pi 2 model B computer running version 3.18 of the Raspbian Wheezy operating system, using version 0.24.7 of the OpenSesame software (Mathôt et al., 2012), and version 2.7.2 of the Python programming language. Video output was via the onboard VideoCore IV 3D graphics processor connected through HDMI, and audio output was via the onboard 900 MHz quad-core ARM Cortex-A7 CPU connected through a 3.5 mm audio connector. For the desktop PC, stimuli were presented using a Windows 7 PC running Matlab R2012b with the Psychophysics toolbox (Brainard, 1997). Video output was via an Asus Striker GTX760, and audio was output via an Asus Xonar DSX sound card. Coincident in time with sound onset, 8-bit TTL pulses were sent to the EEG amplifier by a parallel port cable connected to the stimulus PC computer to mark the data for ERP averaging. For the Raspberry Pi 2, the TTL pulses were sent to the amplifier via a parallel port to serial port cable connected to the GPIO pins, specifically pins 24 and 25.

Each participant completed three blocks of 250 trials for a total of 750 trials. Each trial had a 1/5 likelihood of being a target trial. Each trial began with a pre-tone interval chosen randomly from a uniform distribution between 1000 and 1500 ms, followed by the tone onset. Fig. 1A demonstrates the experimental task, Fig. 1B shows how equipment was setup, and Fig. 1C shows how the Raspberry Pi 2 GPIO pins were wired to the amplifier in order to send the TTL pulses.

2.3. Pre-trial timing adjustment

In a previous pilot study we compared the pre-tone interval and found this delay was longer for the Raspberry Pi 2 compared to the PC ($M_{Pi} = 1.4458$s; $SD_{Pi} = 0.0078$s; $M_{PC} = 1.2925$s; $SD_{PC} = 0.0011$; $t(6) = 52.7625$; $p < 0.001$) despite both experiments being programmed as identical as possible. To ensure that any differences in the ERPs observed were not due to pre-tone interval differences, the interval distribution for the Raspberry Pi 2 was shortened by approximately 160 ms so that the average interval length for the Raspberry Pi 2 more closely matched the PC. Following this correction the Raspberry Pi 2 pre-tone interval was more similar to the PC ($M_{Pi} = 1.2860$s; $SD_{Pi} = 0.0036$s; $M_{PC} = 1.2941$s; $SD_{PC} = 0.0033$; $t(9) = -4.2501$; $p = 0.0021$).

2.4. EEG recording

Recording was done using Brain Products Active Wet electrodes (Brain Products actiCAP adjusted for signal quality). Impedance was not measured directly but inferred from data quality as per the suggested usage guidelines provided by the manufacturer (Brain Products, 2014). All electrodes were arranged in 10–20 positions (Fp2, F3, Fz, F4, T7, C3, Cz, C4, T8, P7, P3, Pz, P4, P8, and Oz). A ground electrode was used and embedded in the cap at position Fpz. Electrolyte gel was applied to this ground electrode. EEG was recorded online and referenced to an electrode clipped to the left ear lobe, and offline the data were re-referenced to the arithmetically derived average of the left and right ear lobe electrodes. Ag/AgCl pin electrodes were used, with SuperVisc electrolyte gel and mild abrasion with a blunted syringe tip used to lower impedances. Gel was applied and impedances were lowered until data quality appeared good (inferred to be around 50 kΩ from past research; Kappenman and Luck, 2010; Laszlo et al., 2014; Mathewson et al., in press). Electrolyte gel was used to lower the impedance of the electrodes on the ears.

In addition to the 15 EEG sensors, 2 reference electrodes, and the ground electrode, the vertical and horizontal bipolar EOG was recorded from passive Ag/AgCl easycap disk electrodes affixed above and below the left eye, and 1 cm lateral from the outer canthus of each eye. Electrolyte gel was used to lower the impedance of these EOG electrodes based on visual inspection of the data. These bipolar channels were recorded using the AUX ports of the V-amp amplifier, using a pair of BIP2AUX converters, and a separate ground electrode affixed to the central forehead.

EEG was recorded with a V-amp 16-channel amplifier (Brain Products). Data were digitized at 500 Hz with a resolution of 24 bits, and filtered with an online bandpass with cutoffs of 0.629 Hz and 30 Hz, along with a notch filter at 60 Hz. The experiment took place in a dimly lit sound and radio frequency attenuated chamber from

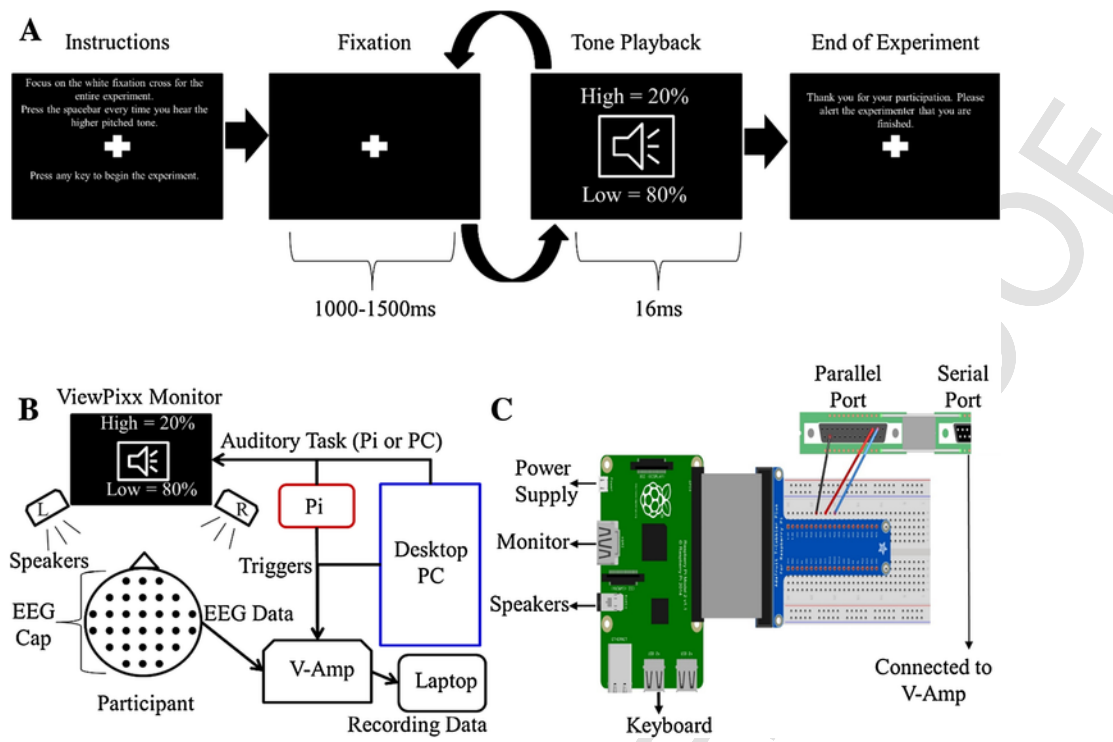

Fig. 1. Experimental task presented and equipment setup. (A) Auditory oddball task presented to participants. 750 tones were played, 80% low and 20% high, and participants responded to rare tone. (B) Set-up of equipment. Participants completed experiment twice, starting with the Raspberry Pi 2 or PC. Triggers sent to amplifier by the Raspberry Pi 2 or PC. EEG data was measured with 16 channel active wet electrode cap and recorded onto a laptop PC connected to the amplifier. Arrows indicate the direction of data transmission. (C) Wiring diagram showing how the Raspberry Pi 2 was connected to the EEG amplifier. An Adafruit Pi Cobbler Kit was used to make the GPIO pins easier to access. GPIO pins 24 and 25 were connected to pins 2 and 3 of the parallel port end of a parallel to serial port adapter cable. The serial port end of this cable was then connected to the EEG amplifier. GPIO pins 24 and 25 were used to send TTL pulses to the amplifier to mark the presentation of low and high tones, respectively. A GPIO ground pin was also connected to the ground pin of the parallel port.

Electro-Medical Instruments, with copper mesh covering the window. The only electrical devices in the chamber were an amplifier, speakers, keyboard, mouse, and monitor. The monitor ran on DC power from outside the chamber, the keyboard and mouse were plugged into USB outside the chamber, and the speakers and amplifier were both powered from outside the chamber. A wireless Logitech K330 keyboard was also in the chamber for use on the Raspberry Pi 2. The lights and fan were turned off, and nothing was plugged into the internal power outlets. Any other devices transmitting or receiving radio waves (e.g., cell phones) were removed from the chamber for the duration of the experiment.

2.5. EEG analysis

Analyses were computed in Matlab R2012b using EEGLAB (Delorme and Makeig, 2004) and custom scripts. The timing of the TTL pulse was marked in the recorded EEG data and used to construct 1000-ms epochs time locked to the onset of standard and target tones, with the average voltage in the first 200-ms baseline period subtracted from the data for each electrode and trial. To remove artifacts due to amplifier blocking and other non-physiological factors, any trials with a voltage difference from baseline larger than ±500 µV on any channel (including eyes) were removed from further analysis. At this time, a regression based eye-movement correction procedure was used to estimate and remove the artifactual variance in the EEG due to blinks as well as horizontal and vertical eye movements (Gratton, Coles, and Donchin, 1983). After identifying blinks with a template based approach, this technique computes propagation factors as regression coefficients predicting the vertical and horizontal eye channel data from the signals at each electrode. The eye channel data is then subtracted from each channel, weighted by these propagation factors, removing any variance in the EEG predicted by eye movements. On average artifact rejection left roughly equal number of trials per participant; Raspberry Pi 2 ($M_{targ} = 144$ *trials;* $range_{targ} = 125–150$; $M_{stand} = 569$; $range_{stand} = 504–600$) and PC ($M_{targ} = 142$; $range_{targ} = 125–151$; $M_{stand} = 578$; $range_{stand} = 530–618$), from which the remaining analyses are computed. No further filtering was done on the data.

3. Results

3.1. Trigger-tone latency

To directly and accurately measure potential latency differences between the TTL pulse onset and tone onset, following the conclusion of the study both tones were played to the speakers and simultaneously attenuated then digitized by the EEG amplifier using custom built hardware. This hardware was connected to the 3.5 mm headphone jack of the Raspberry Pi 2 or PC and would send a unique TTL pulse to the amplifier each time the tone was played to accurately mark tone onset. This setup allowed for direct visualization and measurement of the tone with respect to the TTL pulse. The start of each tone in the digitized recording, in relation to the onset of the trigger sent by the Raspberry Pi 2 or PC, was indicated as the first instance the measured voltage reached positive 1000 µV. Latency between the TTL pulse and tone onset was measured and averaged across 212 trials for the Raspberry Pi 2 and the PC ($M_{Pi} = 34.6710$ *ms;* $SD_{Pi} = 4.7250$ *ms;* $M_{PC} = 45.8250$ *ms;* $SD_{PC} = 0.2803$ *ms*). While the latency was shorter for the Raspberry Pi 2 than the PC (*t(212) = 34.2647;* $p < 0.001$), there was more variability in these latencies. Fig. 2A shows a histogram of the latencies between trigger onset and tone onset for the Raspberry Pi 2 and PC. Fig. 2B shows representative examples of the tones, attenuated and recorded by the amplifier. On average, latency between the TTL pulse and tone was 11.1540 ms (*SD = 4.7397 ms*) longer on the PC than the Raspberry Pi 2. This difference led to temporal offsets in P3 and MMN activity for both systems. In order to minimise variance the triggers for the Raspberry Pi 2 were shifted earlier in time by 11.15 ms to more accurately match the trigger-tone latency of the PC. Subsequent analysis was done using these corrected timings.

3.2. Single trial noise

We estimated the noise in the data on individual trials in two ways. First we computed the average frequency spectra of the baseline period in each EEG epoch, as shown in Fig. 3A. For each participant we randomly selected 504 of their artifact free standard target trials from electrode Pz. For each trial we computed a Fast Fourier Transform by symmetrically padding the 600 time point epochs with zeros to make a 1024 point time series for each epoch, providing frequency bins with a resolution of 0.488 Hz. Because the data are collected with an online 30 Hz low-pass filter, we plot only frequencies up to 30-Hz. Each participant's 504 spectra are then averaged together to compute participant spectra, which were then combined to form grand average spectra plotted in Fig. 3A. Evident from the plot are similar spectra for the Raspberry Pi 2 and PC measurements. Both conditions showed the expected 1/f frequency structure in the data, as well as the typical peak in the alpha frequency range between 8 and 12 Hz (Mathewson et al., 2011).

To compute a second and related estimate of the noise on single trial EEG epochs, we randomly selected 360 standard tone epochs for each participant, and computed the root mean square (RMS) of the baseline period on each trial. We used the 200-ms baseline period (100 time points) prior to trigger onset to avoid the influence of any evoked ERP activity on the RMS measurement. The RMS is a measure of the average absolute difference of the voltage around the baseline, and is therefore a good estimate of single trial noise in the EEG data. For each trial, we averaged the RMS values for each EEG electrode, then averaged over trials for each participant, then computed the grand average RMS across participants (as in Laszlo et al., 2014).

To estimate the distribution of RMS in our data for each condition, we employed a permutation test in which a different 360 epochs were selected without replacement for each participant on each of 10,000 permutations (Laszlo et al., 2014). For each of these random selections, and for each electrode condition, we computed and recorded the grand average single trial RMS. Fig. 3B shows a histogram of the grand average single trial RMS values computed for each permutation, along with a bar graph of the mean and standard deviation. The results suggest a separation between the Raspberry Pi 2 ($M_{RMS} = 6.703;$ SD_{RMS} $EEG = 1.938$) and PC ($M_{RMS} = 6.508;$ $SD_{RMSEEG} = 1.709;$ Wilcoxon rank sum test; $z = -122.472$; $p < 0.0001$) RMS distributions.

To quantify the level of noise in the participant average ERPs, we again employed a permutation test of the RMS values in the baseline period. In this ERP version, for each of the 10,000 permutations, we averaged the 360 standard trials that were randomly selected without replacement from the larger pool of that participant's artifact free trials in each condition. We then computed the RMS of the resultant 100 time points of ERP baseline. We averaged these RMS values over EEG electrodes, and then computed a grand average across participants. Fig. 3C shows a histogram of the grand average RMS values computed in each of the 10,000 permutations in each condition, along with a bar graph of the mean and standard deviation. The Raspberry Pi 2 ($M_{RMS\text{-}ERP} = 0.390;$ $SD_{RMS\text{-}ERP} = 0.108)$ and PC ($M_{RMS\text{-}ERP} = 0.360;$ $SD_{RMS\text{-}ERP} = 0.127$) show similar RMS values (Wilcoxon rank sum test; $z = -66.6773$; $p < 0.001$).

3.3. ERP analysis

Next we examined noise levels in the trial-averaged ERPs. Fig. 4A shows the grand average ERPs from electrode Pz and Fz following standard and target tones. A clear MMN response, a negative deflection occurring between 175 and 275 ms after onset of target tones

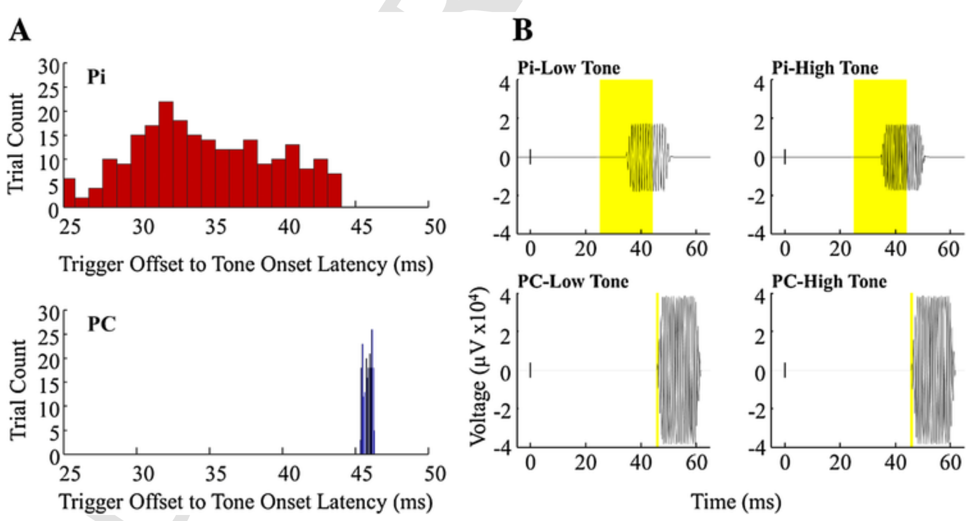

Fig. 2. Trigger-tone latency and tone magnitude for Raspberry Pi 2 and PC. (A) Histogram shows latency between trigger offset and tone onset (ms) across 750 trials for both the Raspberry Pi 2 and PC. Latency was increased but less variable for the PC compared to the Raspberry Pi 2. (B) Plots of high and low tones produced by the Raspberry Pi 2 and PC. Small vertical line represents the average onset of the trigger while the shaded region represents the possible range of tone onset. Again it is clear latency variability is greater for the Raspberry Pi 2. It is also apparent that the volume of the tones produced by the Raspberry Pi 2 (indicated by the voltage magnitude) is less than the PC. We corrected for both the average latency shift and this volume difference, but not the latency variability.

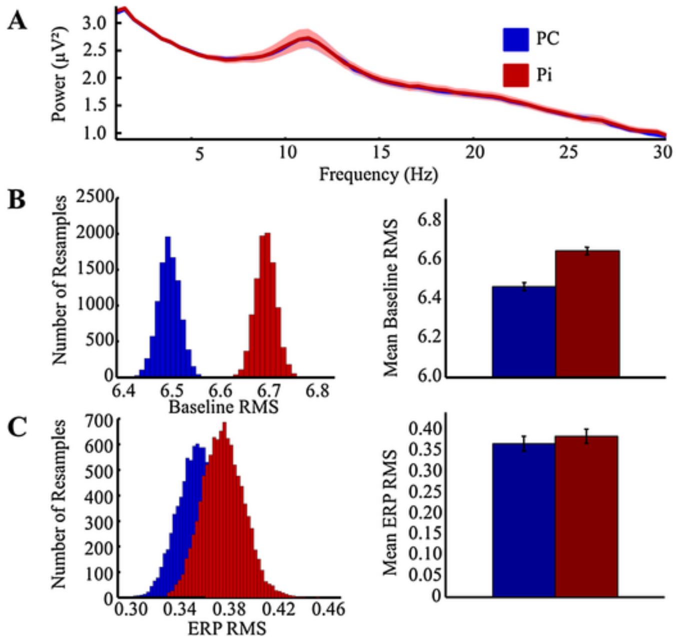

Fig. 3. Analysis of spectra and noise across trials. (A) Spectra plot of power across a 1–30 Hz frequency range. The shaded regions represent standard error of the mean across participants. (B) Histogram of baseline root mean square (RMS) values across 10 000 resampled trials. Bar graph shows mean RMS for the Raspberry Pi 2 and PC, representing the amount of noise present prior to the start of a trial. (C) Histogram of ERP RMS values across 10 000 resampled trials. Bar graph shows mean ERP RMS for the Raspberry Pi 2 and PC. These values indicate the amount of noise present in the averaged ERP signal baseline. Error bars indicate the standard deviation.

that is similar for both conditions, and P3 oddball difference, with more positive voltage between 300 and 430 ms following rare target tones compared to frequent standard tones, can be observed. We used these time windows for all further ERP analyses of the P3 and MMN. Fig. 4B shows the ERPs for standard and target tones overlaid for both the Raspberry Pi 2 and the PC, at electrode locations Pz and Fz.

Fig. 5A shows the difference waves for the MMN and P3, computed by subtracting the ERPs for standard tones from target tones at electrodes Fz and Pz, respectively. For the MMN a negative peak is observed around 270 ms while for the P3 a clear positive peak around 400 ms can be seen. Inset are topographies showing the ERP effects in the indicated time windows, with similar distributions. At electrode Fz, a significant MMN response for the Raspberry Pi 2 ($M_{diffPi} = -2.845\,\mu V$; $SD_{diffPi} = 1.868\,\mu V$; $t(9) = -4.816$; $p < 0.001$) and PC ($M_{diffPi} = -3.083\,\mu V$; $SD_{diffPi} = 1.498\,\mu V$; $t(9) = -6.506$; $p < 0.001$) can be observed. A significant P3 effect at electrode Pz is seen for the Raspberry Pi 2 ($M_{diffPi} = 6.471\,\mu V$; $SD_{diffPi} = 6.332\,\mu V$; $t(9) = 3.232$; $p = 0.0051$) and PC ($M_{diffPC} = 6.081\,\mu V$; $SD_{diffPC} = 5.476\,\mu V$; $t(9) = 3.5118$; $p = 0.00097$).

The MMN ($M_{PC\text{-}Pi} = -0.5708\,\mu V$; $SD_{PC\text{-}Pi} = 1.2130\,\mu V$; $t(9) = -1.4879$; $p = 0.1709$) and P3 windows ($M_{PC\text{-}Pi} = 0.2267\,\mu V$; $SD_{PC\text{-}Pi} = 1.6945\,\mu V$; $t(9) = 0.4231$; $p = 0.6822$) show no significant difference in ERP amplitude between the Raspberry Pi 2 and PC. Fig. 5B shows bar graphs representing the mean and within subject standard error of the MMN and P3 response across participants for the Raspberry Pi 2 and PC.

To test how the trigger-tone latency differences may influence earlier ERPs more susceptible to temporal jitter we examined the N1 response which, based on visual inspection of the grand average ERP waveforms at electrode Fz, was determined to be 130–160 ms following tone onset. The Raspberry Pi 2($M_{Pi} = -1.5943\,\mu V$; $SD_{Pi} = 1.0420\,\mu V$; $t(9) = -4.8384$; $p < 0.0005$) and PC ($M_{PC} = -2.1650\,\mu V$; $SD_{PC} = 0.8911\,\mu V$; $t(9) = -7.6829$; $p < 0.0001$)

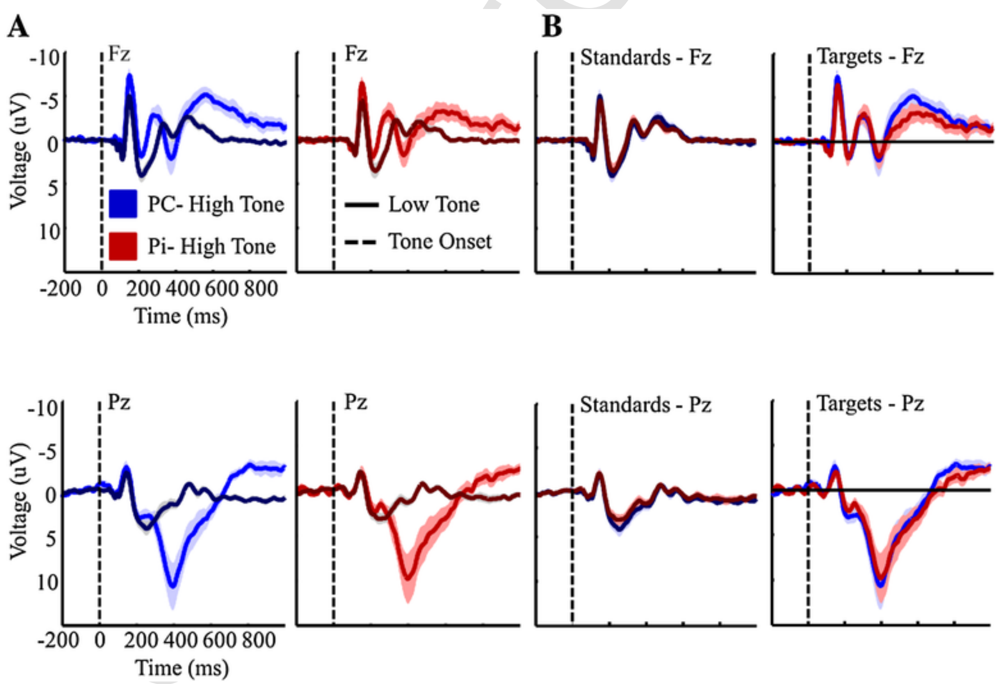

Fig. 4. Event related potentials (ERP) obtained from the Raspberry Pi 2 and PC across electrodes Fz and Pz. (A) Four leftmost plots show the average ERPs measured following presentation of a high or low tone at electrode Fz and Pz. (B) Four rightmost plots offer a comparison between the Raspberry Pi 2 and PC, showing the average ERPs following the high tone. The ERPs derived from both systems appear spatially and temporally similar, but for a bit of attenuation in the later large components in the Raspberry Pi 2, error bars indicate the within subject standard error of the mean.

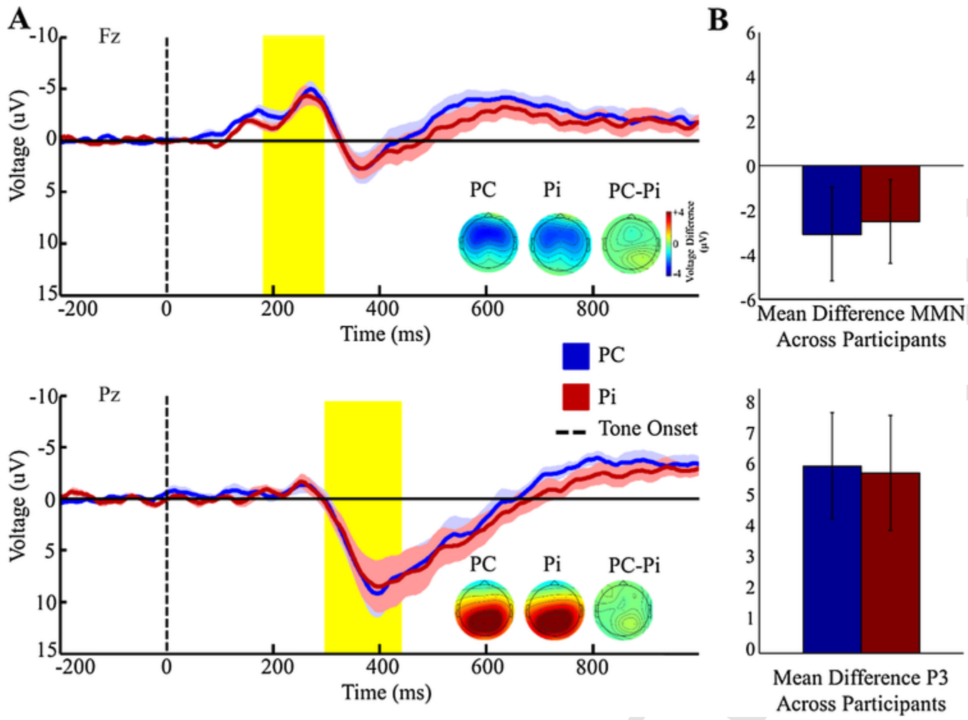

Fig. 5. Difference in ERPs evoked from Raspberry Pi 2 and PC. (A) Difference wave plots (low tone ERP − high tone ERP) at electrodes Fz and Pz for both the Raspberry Pi 2 and PC. Topographical plots show MMN and P3 responses for the Raspberry Pi 2 and PC. Plots were derived using the appropriate time windows indicated by the shaded yellow regions. Error bars represent the within-participant standard error since within participant variation has been removed due to the subtraction (Loftus and Masson, 1994). (B) Bar graphs indicate the average MMN and P3 response across participants for the Raspberry Pi 2 and PC, error bars indicate the within subject standard error of the mean. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

show significant N1 responses. While the Raspberry Pi 2 showed a reduced N1 compared to the PC, this difference was on the edge of significance (*t(9) = −2.3295;* p = 0.0448).

3.4. ERP power

To compare the ERP statistical power as a function of the number of trials used for both the P3 and MMN, we used another permutation procedure in which we varied the number of trials contributing to the ERP average while keeping the 4 to 1 ratio of standard to target trials (Mathewson et al., in press). Trial numbers were varied from 4 standards and 1 target trial, by 20 standard trials, up to 540 standard and 135 target trials, separately for each of the two stimulus presentation conditions. For each number of trials, 10,000 permutations were randomly selected from the total pool without replacement.

For each permutation, the selected single trials were averaged to create participant ERPs separately for target and standard tones. The difference between target and standard tones was then computed at electrode Fz between 175 and 275 ms (MMN) and electrode Pz between 300 and 430 ms (P3), and these simulated participant average ERP differences were compared to a null distribution with a standard *t*-test (df = 9, one-tailed, $\alpha = 0.05$). Fig. 6 plots the proportion of the 10,000 permutations in which the *t*-statistic passed the significance threshold, as a function of the number of samples in each permutation. The P3 and MMN data from the Raspberry Pi 2 and PC reached significance on 80% of permutations (80% power dashed line) with similar numbers of trials. On average fewer trials are needed to reach 80% power for the PC (MMN trials = 32, P3 trials = 24) condition compared to the Raspberry Pi 2 (MMN trials = 56, P3 trials = 32).

4. Discussion

We directly compared a Raspberry Pi 2 computer to a traditional desktop PC to assess if the Raspberry Pi 2 can act as a viable, low-cost alternative in presenting stimuli for EEG experiments and producing reliable ERP measurements. This comparison was done using an auditory oddball task which has been shown to reliably produce ERPs such as the MMN and P3 in response to rare target tones. Despite differences in trigger-tone timing quality EEG data and significant ERP responses were obtained on the Raspberry Pi 2 and are comparable to the desktop PC.

Trigger to tone onset timings were on average 11.15 ms shorter for the Raspberry Pi 2 compared to the PC; however, the Raspberry Pi 2 also showed more variability in these timings. This variation seems unusual considering the PC we used had significantly higher processing power compared to the Raspberry Pi 2 but hardware and operating system (OS) differences likely account for the increased variability in trigger to tone latencies observed. The Raspberry Pi 2 is running the Raspbian OS, a modified version of Debian which is based on the Linux OS, specifically designed for Raspberry Pi devices. The PC is running Windows 7 and is designed to run on a variety of devices rather than on a specific hardware configuration. The specialised OS for the Raspberry Pi 2 may help to lower the average trigger to tone latency compared to the PC, but the increased variability is likely due to the very different hardware of both systems. On the PC tone generation was done using PsychPortAudio from PsychToolBox and, according to the website (InitializePsychAudio, 2012), there are latency issues associated with Windows that are not present in Linux based systems. In terms of hardware, the Raspberry Pi 2 has a slower processor (900 MHz quad-core) compared to the PC

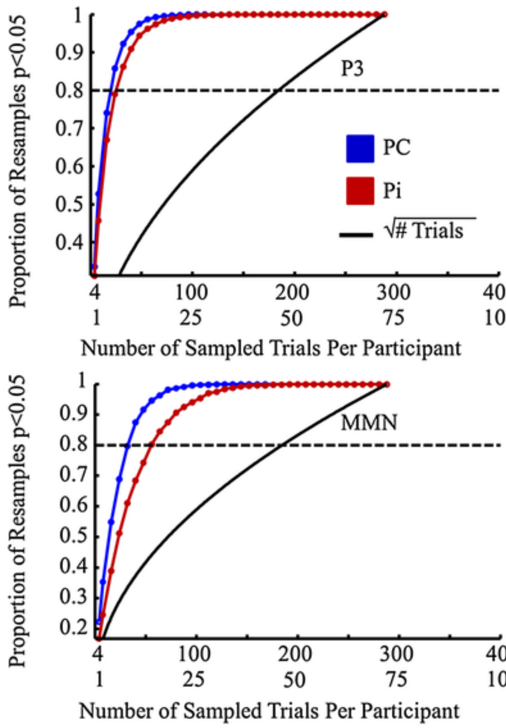

Fig. 6. Statistical power for the Raspberry Pi 2 and PC in obtaining significant ERP responses. Number of resamplings with significant MMN and P3 responses on both the Raspberry Pi 2 and PC as a function of the number of trials. The same 4:1 ratio for tone presentation was kept during resampling. The dashed line signifies 80% statistical power. Slightly fewer trials were needed to obtain 80% statistical significance for the Raspberry Pi 2 compared with the PC.

(3.6 GHz octa-core) while also having less RAM available (1GB compared to 16GB). However, the Raspberry Pi 2 also has fewer processes running simultaneously so while there is less demand on the Raspberry Pi 2, any demand may have a greater performance impact compared to the PC. The PC is also using a dedicated sound card to generate the tones which may help decrease variability but also slightly increase the time it takes to generate a tone since the sound card is another device the PC must interface with. Differences between the Matlab and Python programming languages will also contribute to the observed differences. More powerful hardware (as in the newly released Raspberry Pi 3) and further decreasing demands on the processor (such as programming the experiment directly in Python for both systems) will help to minimise any differences observed.

To understand how these latency differences may interfere with the amplitude and measurement of earlier ERPs which may be more susceptible to more variable latencies, we showed that both the Raspberry Pi 2 and PC can present stimuli that elicit a reliable and significant N1 response. While the amplitude of the N1 was lower for the Raspberry Pi 2 compared to the PC, this difference was not significant. This decreased amplitude is likely influenced by the more variable latencies of the Raspberry Pi 2 since the peak of the N1 response is shorter compared to the MMN and P3 and thus more susceptible to temporal jitter. Smaller, shorter ERPs could essentially be ‘averaged out’ due to this jitter, making the Raspberry Pi 2 less suitable for such tasks. Minimising latency variability would be essential for such tasks and the measures mentioned previously should help minimise this variability and make the Raspberry Pi 2 suitable for a wider range of ERP related research.

We also observed increased noise during both the baseline and ERP measurements for the Raspberry Pi 2. While the noise difference was not significant for the ERP RMS, background noise was significantly different with higher baseline noise for the Raspberry Pi 2 than the PC. This increase in noise may be due to sound quality and volume differences between both computer systems; the Raspberry Pi 2 requires less power to run and likely cannot provide as much power to the speakers as compared to the PC when producing the auditory tones. In order to match tone volume for both systems, and to make the Raspberry Pi 2 as similar to the PC as possible, the volume on the speakers was directly increased during the Raspberry Pi 2 until the tone volume matched that of the PC. This volume increase also amplified any static noise which could be heard when a tone was not playing, and may account for the increased noise in the Raspberry Pi 2. The PC used a dedicated sound card to produce the tones, compared to the Raspberry Pi 2 which relied solely on the CPU for sound playback. Using dedicated hardware to produce the tones likely resulted in cleaner, louder sounds for the PC. Further, increased variance between trigger onset and tone onset for the Raspberry Pi 2 would result in more variable baseline measurements across each trial compared to the PC baseline, which would be more consistent.

If these noise and timing differences for the Raspberry Pi 2 had been more significant, the ERPs measured would have been temporally and spatially different from those obtained by the PC. Large, unreliable temporal variability may prevent significant MMN or P3 responses from being measured, which would suggest that the Raspberry Pi 2 could not reliably be used for stimulus presentation in EEG experiments and could not act as a viable replacement for a desktop PC in certain situations. Despite this temporal smearing, ERPs were not significantly different; stimulus presentation using the Raspberry Pi 2 produced spatially and temporally similar MMN and P3 ERPs, along with similar scalp topographies. Our test of statistical power (Kappenman and Luck, 2010; Laszlo et al., 2014; Mathewson et al., in press) show that similar numbers of trials are needed to reach a statistical power of 0.80, with the Raspberry Pi 2 requiring slightly more trials and is likely due to the latency and auditory differences mentioned previously. No external modifications were made to adjust for the increased variability of the Raspberry Pi 2 as our goal was to measure the impact of this less precise presentation on ERP recording and analysis, and to show that reliable P3 and MMN responses could be measured despite these differences. The use of our custom hardware, similar to the work by Badcock et al. (2015) and de Lissa et al. (2015) where the tone itself initiates the TTL pulse, would likely alleviate these latency issues but would defeat the goal of the current experiment, which is to strictly compare the Raspberry Pi 2 to a PC without adding extra components.

Other portable electronics may also fulfill the role of making experiments more mobile but the Raspberry Pi 2 offers several distinct advantages. Smart phones and tablets are very portable and can present tones for the oddball paradigm while a laptop offers the same basic functionality of a desktop PC, but they are much more expensive and lack the customisability a Raspberry Pi 2 offers. The Raspberry Pi 2 offers several full size USB ports to connect external peripherals, such as keyboards and mice, and multiple ways to connect external displays and auditory equipment, but the programmable GPIO pins allow for a level of customisability currently not offered by the other devices. For our experiment these pins were used to directly send TTL pulses to an external EEG amplifier but they can be used for many other projects such as lighting LEDs, receiving temperature, heart rate, and galvanic skin response measurements, and they can also be used to control small electronic motors. Packages are available in Python to easily and directly program these pins. The Arduino microcontroller offers similarly customisable GPIO pins, with external attachments offering greater possibilities, but these pins must be programmed from an external device. Experiments can be programmed and run entirely from the Raspberry Pi 2, offering a high degree of customisability not matched by many other portable electronics.

Demonstrating its portability and reliability, the Raspberry Pi 2 has been used to derive ERPs while participants rode a bicycle outside. Scanlon et al. (in preparation) performed a similar auditory oddball task with the Raspberry Pi 2 while participants peddled a bicycle outside, with all necessary equipment placed inside a backpack worn by the participant. Significant MMN and P3 responses were obtained and comparable to those derived from a laboratory setting, demonstrating that the Raspberry Pi 2 computer can reliably administer EEG experiments in a variety of settings and mobile applications. The increased use of portable and inexpensive EEG equipment in the field, combined with stimulus presentation solutions such as those presented here, will increase the cost of entry to ERP research.

The present study demonstrates that a Raspberry Pi 2 computer can present stimuli used in an auditory oddball paradigm, producing comparable ERPs to an experiment administered by a traditional desktop PC. While differences are apparent between both computer systems, results from the Raspberry Pi 2 remain comparable to a PC, and further changes to the experiment and equipment will likely minimise these differences. The Raspberry Pi 2 can serve as a dependable and low cost alternative to a traditional desktop PC in presenting stimuli for EEG experiments, allowing for more mobile EEG experiments with results that are applicable to a wider variety of settings and conditions.

Uncited reference

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