Brain Waves Control Devices with Brain Computer Interface (BCI): Implications on Security and Privacy

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Comparison of Brain Computer Interface (BCI) Devices based on Security and Privacy Implications

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ABSTRACT

Brain Computer Interface (BCI) technology represents a highly growing field of research with application systems. BCI systems typically receive unique brain signals and processes them translate them into commands to output devices which carries out desirable actions. On the same token, BCI presents an opportunity to augment existing authentication methods to address various security and privacy concerns inundating the marketplace. Although Brain Waves Control Devices as potential biometric for person identification in addressing privacy and security concerns has been extensively studied, the role of BCI in addressing security concerns using Brain Waves Control Devices is relatively in its infancy. We found that the implementation of BCI system in the context of Brain Waves Control Devices in addressing security and privacy concerns is currently at its infancy. In this paper, we also examined 20 mainstream Brain Waves Control Devices in the form of electroencephalography (EEG) in relation to its potential use with BCI to potentially address security and privacy concerns. We conclude that there is still much work that needs to be done when interpreting results from mainstream Brain Waves Control Devices in the context of BCI systems to effectively address security and privacy concerns. However, BCI offers the best possible hope and opportunity to optimises brain signals using signal processing and decoding techniques as feedback mechanisms to improve the performance of the BCI applications and realise the overarching goal of addressing privacy and security concerns.

Keywords: BCI (Brain Computer Interface), Brain Waves Control Devices, Security and Privacy

INTRODUCTION

One of the most exciting areas of BCI research is the development of devices that can be controlled by thoughts. There are varying challenges to the implementation of BCI. An extreme challenge is perhaps interpreting the brain signals for movement in someone who can't physically move their own arm. Figure 1 shows the signal acquisition methods which the signal can be separate as invasive and non-invasive (Waldert, 2016). In the invasive methodology, it can have the cortical surface (ECoG) and intracortical. The non-invasive signal methodology will include EEG, MEG, fMRI and fNIRS(Cincotti et al., 2008)

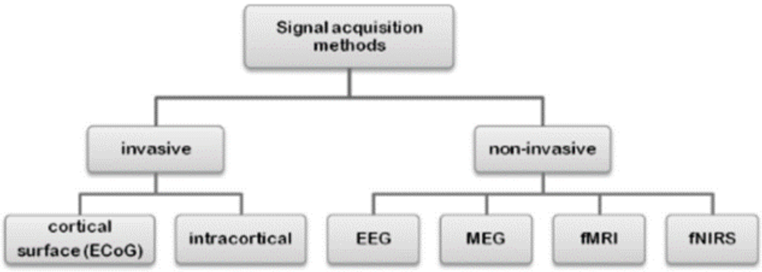

Figure 1. Signal acquisition methods

BCI is used for translating brain signals to devices with desired actions from the user. The research of BCI systems has grown rapidly from pas 15 to 20 years (Waldert, 2016). In essence, Brain Waves Control Devices (i.e. EEG) is the hardware to “catch” our brain waves and translate them into commands for the desired action.

In this paper, we will first examine the subject of BCI. This is followed by an understanding of how BCI has been used across domains. We subsequently conduct an in-depth review of various Brain Waves Control Devices given that there are many Brain Waves Control Devices in the market. In this study, our focus is only on a particular type of Brain Waves Control Device product, i.e. EEGs. These products are subsequently analysed, and their results presented in the context of how they fare in relation to BCI and the overarching goal of addressing privacy and security concerns. We conclude the paper with a discussion on the effectiveness of Brain Waves Control Devices with Brain Computer Interface (BCI) by presenting opportunities and implications for further research in relation to user security and privacy.

BCI Definition and Typical Applications

Brain-computer interfaces (BCIs) typically analyse brain signals and translate those signals into commands for the devices required for actions (Waldert, 2016). The research on BCI is slowly gaining traction over the last 15 to 20 years (Cincotti et al., 2008; Waldert, 2016). BCI systems measure brain signals and translate them to device signals (King et al., 2011). On the other hand, a voice control system which uses voice to give commands cannot be considered as a BCI. Brain signals for BCI can be recorded with non-invasively sensors outside our head or with implanted electrodes; the most common devices for apply BCI is electroencephalography (EEG) (Cincotti et al., 2008). EEG machines on its own are not BCI because this device only can record brain signals and not provide output to react from the user's environment (Waldert, 2016). Figure 2 demonstrates the flow illustrating the fact that soon after the EEG devices received the signals from the brain, it will start with the pre-processing, feature extraction and feature classification and then to do the commends for the interface system.

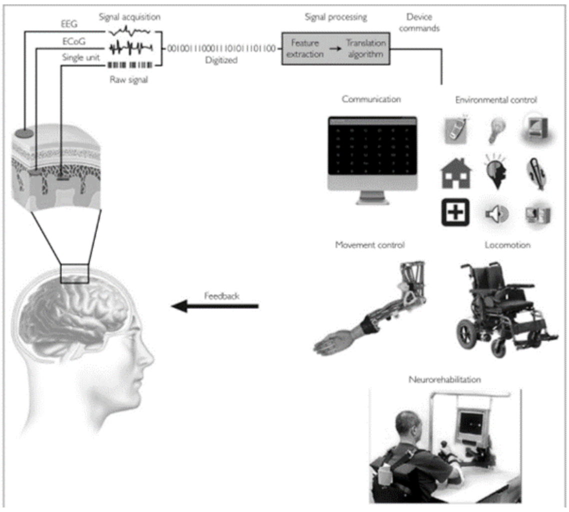

Fig 2. Components of a BCI system (*Waldert, 2016)*

Other non-invasive techniques which also used commonly in the research are functional MRI (fMRI), functional near-infrared spectroscopy (fNIRS), both measure the hemodynamic responses for the active area inside our brain. The BCI application can be applied in various field as it is shown in figure 3.

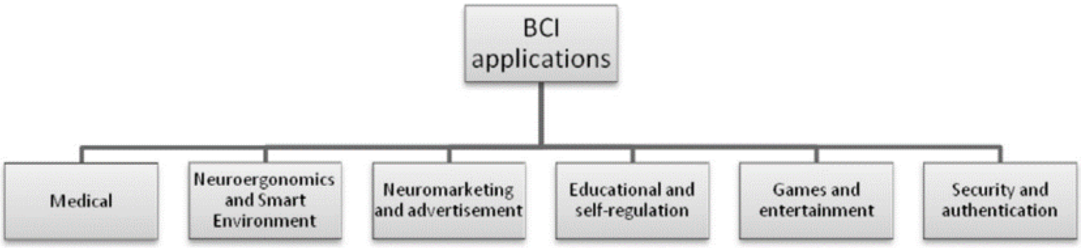

Fig. 3. BCI Applications *(Rao & Scherer, 2010)*

Medical applications can monitor the health condition according to the brain signals activities. The early use of the BCI was in biomedical application and was subsequently applied in area of assistive devices (Rao & Scherer, 2010). BCI-driven assistive devices have helped challenged or physically disabled people (Bi et al., 2013). BCI-driven assistive devices were able to assist non-paralyzed humans when integrated with existing medical applications (Bi et al., 2013).

Fig. 4. Usage of BCI in medical field phases *(Hanafiah, Taib, & Hamid, 2010)*

Figure 4 exemplifies the use of BCI in medical field phases. The authors (Hanafiah, Taib, & Hamid, 2010; Mumtaz, Vuong, Xia, Malik, & Rashid, 2017) have explained brain signal detection and analysis can aid in the prevention in the smoking, alcoholism and motion sickness. Additionally, using EEG based machine like MRI and CT-SCAN presence of tumours can be detected (Selvam & Shenbagadevi, 2011; Sharanreddy & Kulkarni, 2013; Poulos, Felekis, & Evangelou, 2012). For the people with mobility issues, BCI system will help them with rehabilitation and restoration with their mobilities and functionalities(Fadzal, Mansor, & Khuan, 2011; Koch et al., 2013).

Neuroergonomics and smart environments such as smart home, office or transportations can be applied using BCI systems with a better living environment. Internet Of Things (IOT) can be combined with BCI devices to improve the functionality of the devices (Domingo, 2012). Smart living environments also can be combined with the BCI system. Such us the auto-adjustment control system (Ou, Lin, Chang, & Lin, 2012). BCI also can be applied in the working environment to analyse workload and efficiency by analysing brain signals (Roy, Bonnet, Charbonnier, & Campagne, 2013). Another field can be applied BCI is transportation and human safety. By analysing the driver brain signals, it will help with mitigate accidents and traffic (Dong, Hu, Uchimura, & Murayama, 2011; Wang, Chen, & Lin, 2014).

Neuromarketing and advertisement also can be applied with BCI systems. Authors in explained how the TV advertisements benefit from using the EEG system. BCI system can analyse the user watching activities and by analysing the impact, it helps with the advertisement result (Vecchiato et al., 2009; Hata et al., 2018).

People interaction with each other can be detected through the BCI system which can be used in the education and self- regulation field (Sorudeykin, 2010) .EEG can also be applied in sports or stress in the examination (Johnston, Boehm, Healy, Goebel, & Linden, 2010). Birbaumer, Ruiz, & Sitaram (2013) espoused how BCI can be is used in self-regulation and learning behaviour.

Entertainment and games and be used for BCIs. Games which that use helicopters to fly from point to point generated by the brain signals (Royer, Doud, Rose, & Bin He, 2010). On the other hand, EEG signals can also help with neuroprosthetic rehabilitation.

Security and Authentication in BCI Products

Security system usually uses knowledge-based, object-based or biometrics-based authentication methods. Brain signals also can be applied in the authentication field which also unique and identical ("(PDF) Two Factor Authentication using EEG Augmented Passwords," n.d.; Revett, Deravi, & Sirlantzis, 2010). Security risk such as simple insecure password, shoulder surfing, theft crime and cancellable biometrics are often seen as limitations of mainstream authentication methods (Khalifa, Salem, Roushdy, & Revett, 2012). Brain signals are secure sources for information authentication. It provides solutions for current risks (Karthikeyan & Sabarigiri, 2011).

Švogor & Kišasondi (n.d.) espoused the use of EEG products to enhance the password with the brain signals which with the user's mental state. The advantage of using the brain signals for the authentication because it is not easily replicated by other users which will also be useful for people with special memory conditions (Revett et al., 2010). Since brain signals are known to be unique, can be used as part of biometric systems to protect users' identify and profile and potentially address privacy and security concerns.

BCI and Brain Waves Control Devices to address Privacy and Security Concerns

The premise behind Brain Computer Interfaces (BCIs) is the fact that it represents a direct communication link between the brain and an external device. Experimental results have shown how electroencephalographic (EEG) signals, recorded from consumer-grade BCI devices, can be used to extract private information about a user (Birbaumer, Ruiz, & Sitaram, 2013). The experimental results come does not come as a surprise given the increasing need to understand data from an organization point of view in terms of rich data extracted from BCI devices. The concern is, however, on the eventual use of such data. It is unsurmountable to accept that rich information is laid bare. On the same note, it is arguable that with sufficient computational power, this information can be exploited by others to make inferences about our memory, intentions, conscious and unconscious interests, as well as about our emotional reactions. Suffice to say that privacy and security issues arising from the misuse of BCI devices are an important issue that deserves immediate attention and careful consideration. Figure 5 illustrates the typical architecture of a BCI system taking into account security and privacy concerns here.

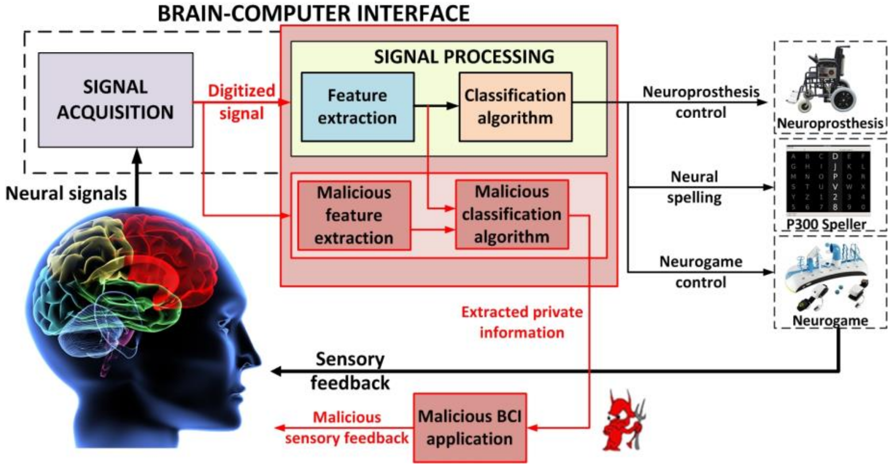

Fig. 5. Security and Privacy Implications of a typical BCI System *(Abdulkader, Atia, & Mostafa, 2015)*

METHODS

Given that the main functions for the BCI to record the brain waves and then translate those signals to the computer system to do the desired action, it is counterintuitive to examine BCI without a careful examination of prevailing Brain Waves Control Devices and its function to address security and privacy concerns. The method that been used for this paper is a quantitative one. We examined 20 mainstream Brain Waves Control Devices in the form of electroencephalography (EEG) in relation to its potential use with BCI to potentially address security and privacy concerns. The data was obtained mostly from insigghts from mainstream research papers augmented with data from vendors sites for product specific details.

Brain activity can be captured by various methods available to practitioners today. Most of them are quite expensive and require a lot of time and effort, and hence cannot be used as a basis to mitigate security and privacy concerns. EEG method, however, is the most extensively studied for person identification. Traditional devices for Brain Waves Control Devices like EEG recording are bulky & relatively expensive too. Having said that technology had moved forward, and cheaper and more convenient devices are now available. EEG, however, remains the most popular given that many organisations and institutions have already invested in them. Therefore, the data from the analysis of Brain Waves Control Devices were solicited from existing mainstream EEG products (although not exhaustive) since it is most commonly used for the longest time. Hence, we considered only mainstream EEG devices as the preferred Brain Waves Control Devices for the purpose of the research.

RESULTS

The section on the Appendix provides a detail illustration of 20 mainstream Brain Waves Control Devices in the form of electroencephalography (EEG). Most of the 20 products examined have been reported to demonstrate seamlessly in its useful (i.e. collection of raw data) allowing for better prospects to analyse and synthesise raw date. Another key observation of the 20 products demonstrate is that they were rather domain specific. Additionally, much of these products have been used largely for entertainment or medical purposes and therefore cannot be used in its present form to mitigate security and privacy concerns.

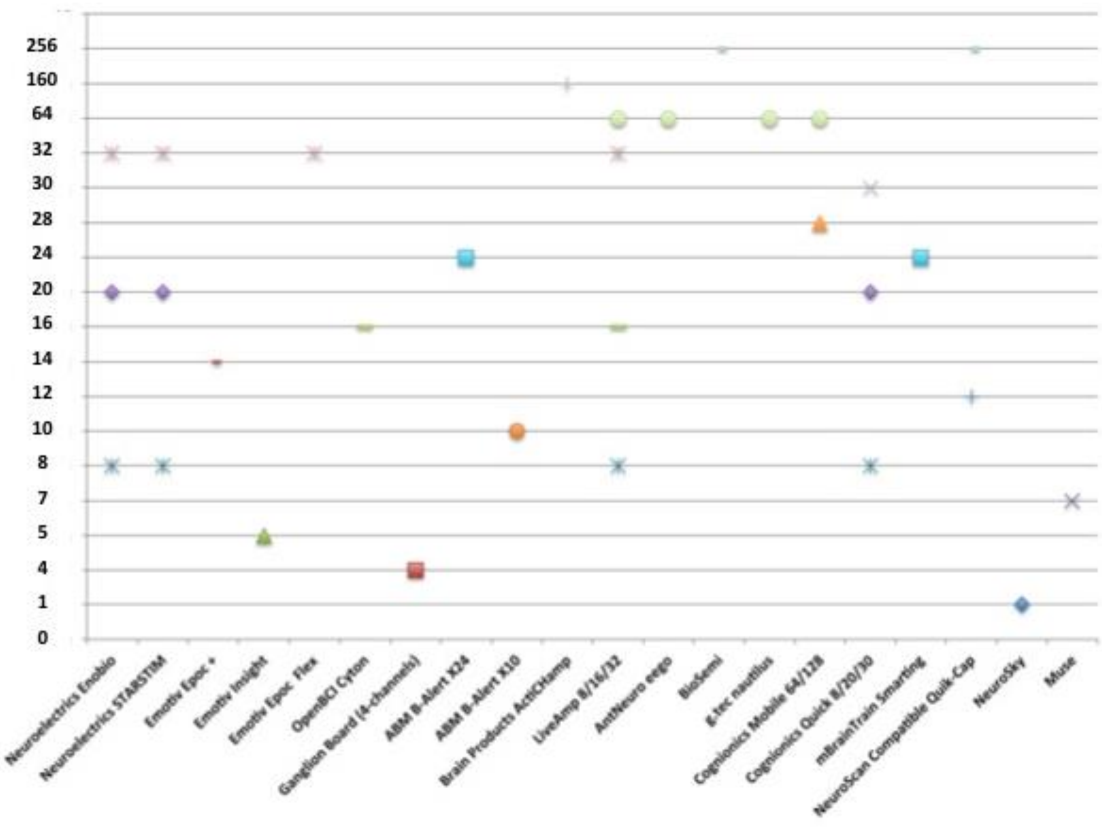

Fig. 6. BCI devices based on number of channel

By analysing 20 mainstream Brain Waves Control Devices, we can identify prominent elements of these devices with regards to number of channels, type of communication, operating time as well as price range of the devices under evaluation. Figure 6 illustrates the distribution of BCI devices based on number of channels. Out of 20 BCI devices evaluated, 5 devices offer multi- channels EEG recordings ranging from 8 to 64 channels. The highest number of channels (256 channels) is supported only by 1 BCI device known as BioSemi. Other 8 devices offer single channel EEG recordings with the lowest being 10 channels and the highest is up to 160 channels. It is also interesting to note that 1 device (Muse) offers 7 channels; with each channel finely calibrated sensors for higher accuracy. The highest number of channel frequencies per device is 4 with 8, 32 and 64 channels respectively

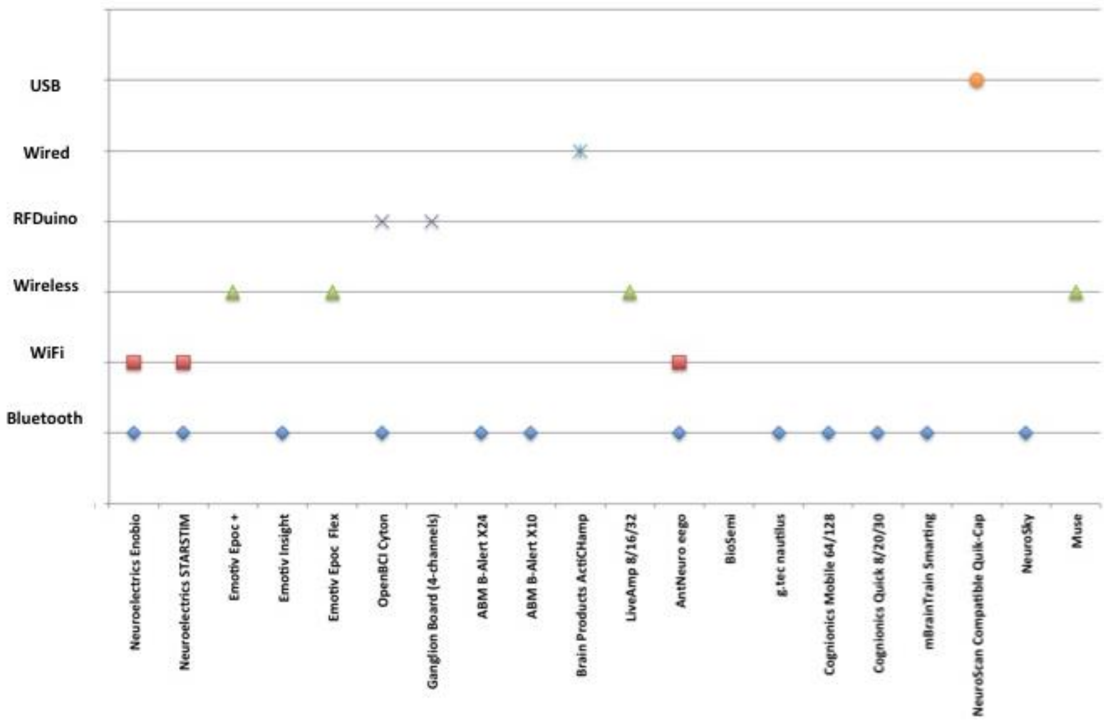

Fig. 7. BCI devices based on type of communication

We can observe from Figure 7, Bluetooth is the most popular mode of communications to transmit EEG signals with 60% of evaluated devices providing it as a communication option. While wired and USB is the least popular mode of communication with only Brain Products ActiCHamp offering the communication option for wired, and NeuroScan Compatible Quick-Cap for USB. Majority of the devices only provide one mode of communication, however it is noticeable that 4 devices offer more than one option as mode of communication. The option of multiple mode of communication for these 4 devices ranges from the combination of Bluetooth, WiFi and RFDuino.

Looking at the longevity of operating time, 15% of the devices has the lowest number of operating time with 4 hours. This is reflected as per Figure 8. 20% of devices have various operating time based on mode of communication of the device during the time in use. It ranges from 6 – 16 hours depending on the mode of communication the device is using at the point of time. It is observed that these devices are able to operate for longer hours upon using SD card compared to using Bluetooth. Another valuable information that can be extracted from Figure 8 is out of 20 devices, only 1 device (NeuroSky) provide the capability to operate using AAA battery with an estimation of 8 hours of operating time on battery.

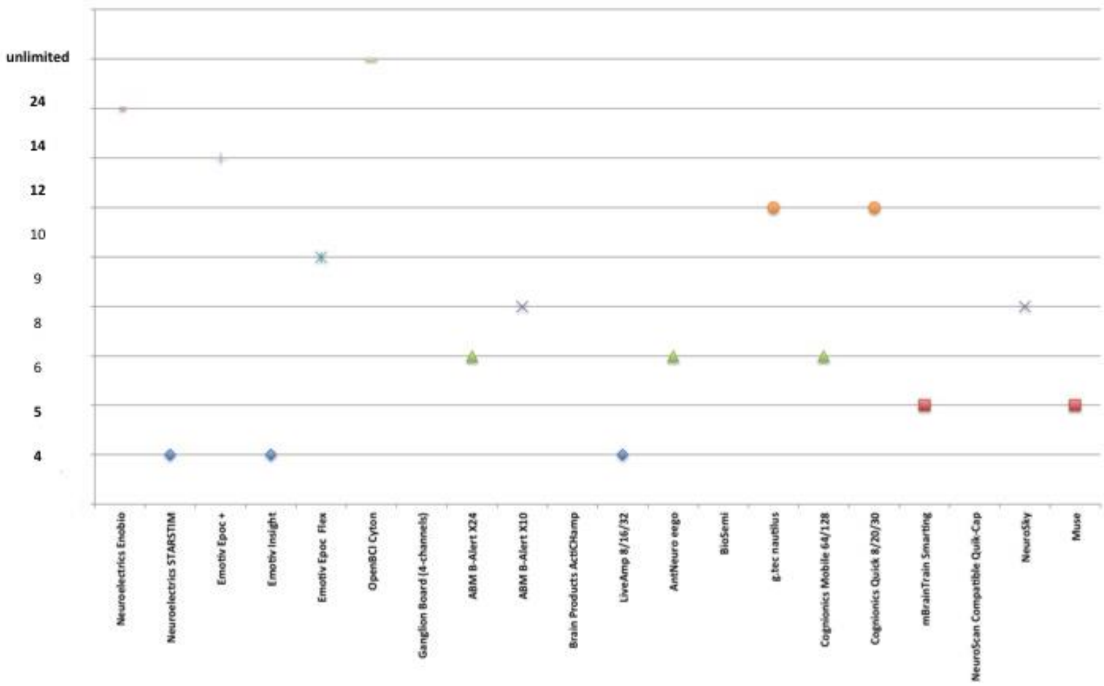

Fig. 8. BCI devices based on Operating Time

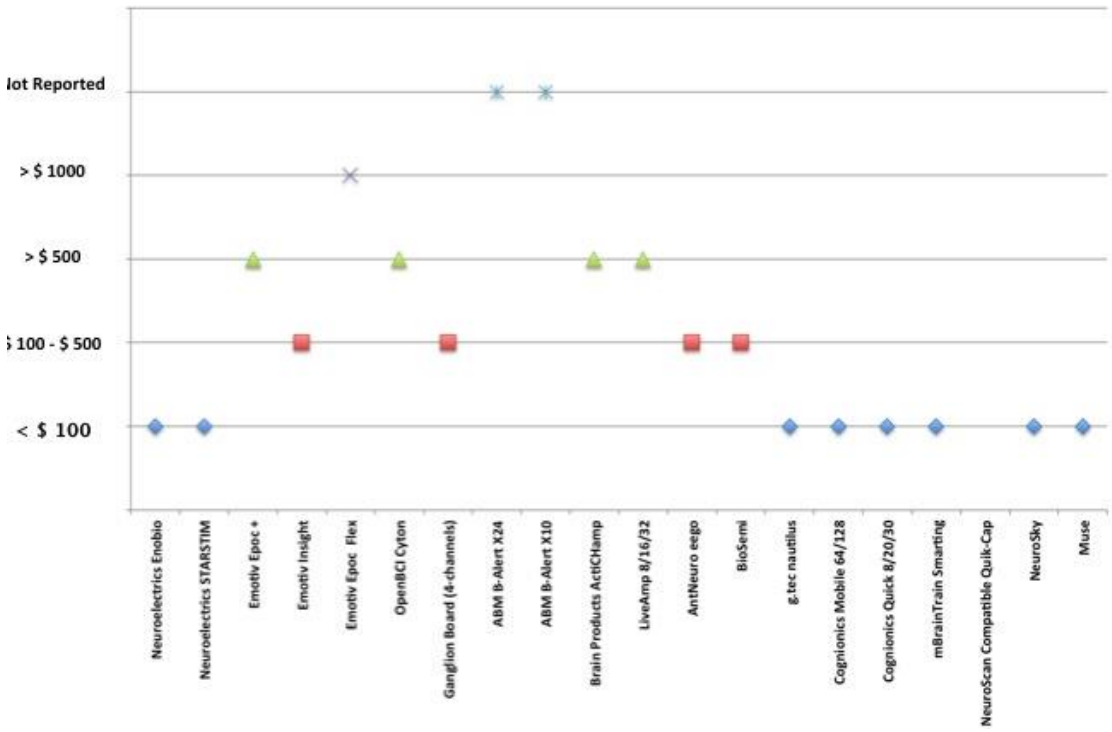

Fig. 9. BCI devices based on Price

Figure 9 compares the BCI devices based on price. Based on the result shown, we notice that 40% of devices are priced reasonably below USD100 while 40% are priced between USD100-USD1000. The only device within the high range of price is Emotiv Epoc Flex, priced above USD1000. However, the result is lacking price information of 2 devices as the information pertaining price is not reported for these devices.

The product details research has been shown in a table format as seen in the Appendix. The result has been shown that most of the popular BCI systems are mainly used in entertainment or medical purpose. However, BCI applications did not cater towards security authentication let alone addressing security and privacy concerns.

We conclude that there is still much work that needs to be done when interpreting results (in Appendix) gathered from mainstream Brain Waves Control Devices (EEG in this case) to answer the overarching question if Brain Waves Control Devices can be effectively used in its current form to address security and privacy concerns. The findings in the section under Appendix also, cannot be used readily to extrapolate if prevailing Brain Waves Control Devices (EEG in particular) allows for easier extraction of physiological characteristics (for security and privacy concerns).

CONCLUSION

BCI applications have undoubtedly grown in popularity partly driven by various success stories across domains. The success of BCI in medical, transportation, games, entertainment domains in being able to successfully transmit signals from Brain Waves Control Devices as an input to facilitate various BCI functional features is truly commendable. Nonetheless, the application of Brain Waves Control Devices in BCI inundating the marketplace has been predominantly limited and restricted to the medical, transportation, games, entertainment domains. Despite BCI’s many benefits and promise it offers, there are hardly any vendors developing solutions integrating Brain Waves Control Devices using BCI for the purpose of authentication and validation of confidential data. On the same note, there are hardly any manufacturers of Brain Waves Control Devices providing useful extensions to address pressing security and privacy concerns effectively. Although Brain Waves Control Devices (i.e. EEG devices) analysed in this paper (see Appendix) have been proven in it's effective and accuracy across most domains, the challenge remains if the same devices could be used as a basis to address and complement existing approaches to mitigate security and privacy concerns. Hence, we would like to present a case that despite the rise of BCI applications that relate to existing Brain Waves Control Devices in general and EEG products in particular, there is a lack of research and breakthrough on how the same can be realised in addressing security and privacy concerns. In short, with the goal of identifying the brain signals, the Brain Waves Control Devices can provide for a more secure basis of authentication to address security and privacy concerns which must not only be researched and investigated further but be made a basis for the development of future Brain Waves Control Devices. However, efforts to the realise the goal is heavily dependent cost, accuracy, proven algorithms and operational challenges given that its impact will have far-reaching consequences particularly on mission-critical applications and real-time systems. It is also interesting to understand if the data obtained from existing EEG devices can be used as a good classifier to provide useful input to BCI systems which form an area for future research. The authentication mechanism using brain waves can also be a subject of future work. Therefore, further research will have to be undertaken in relation to the impact and effectiveness of BCI and Brain Waves Control Devices to address security and privacy concerns.

However, what is certain is that more than any other approach, BCI offers the best possible hope in being able to optimise brain signals using signal processing and decoding techniques as feedback mechanisms to improve the performance of the BCI applications and therefore realise the overarching goal of addressing privacy and security concerns.

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APPENDIX

No	Product Name	Number of Channels	Sampling Rate	Communication	Operating Time	Weight	Medically Certified	Price	Year	Country	Company
1	Neuroelectrics Enobio	8/20/32	500 Hz	Bluetooth / WiFi	14 hours	65 g	CE / FDA	$$	2011	Barcelona (Now Boston)	Neuroelectrics
2	Neuroelectrics STAR STIM	8/20/32	500 Hz	Bluetooth / WiFi	4 hours	65 g	Yes	$$		Barcelona (Now Boston)	Neuroelectrics
3	Emotiv Epoc +	14	128 Hz	Proprietary wireless	12 hours	125g	No	$799.00	2011	San Francisco, U.S.A.	Emotiv
6	OpenBCI Cyton	16	250 Hz	Bluetooth / RFDuino radio	24 hours	260g	No	$ 499.99	2013	Brooklyn, NY	OpenBCI
8	ABM B-Alert X24	24	256 Hz	Bluetooth	6 hours Bluetooth / 16 hours SD card	110g	No	NA	15 years ago	Carlsbad, CA	ABM
9	ABM B-Alert X10	10	256 Hz	Bluetooth	8+ hours	110g	No	NA	15 years ago	Carlsbad, CA	ABM
10	Brain Products ActiCHamp	Up to 160	100 kHz	Wired	Unlimited (wired)	1.1 kg	No	$$$	1997	Germany	Brain Products
11	LiveAmp 8/16/32	8/16/32/64	1000Hz	wireless	4 hours	60 g	No	$$$	1997	Germany	Brain Products

12	AntNeuro eego	64	2048Hz	Yes (Bluetooth / WiFi)	6 hours	500g	CE	$$	1997	Netherlands	ANT Neuro
13	BioSemi	256	2-16kHz	No	5 hours (or unlimited when wired)	1.1 kg	No	$$$	1998	University of Amsterdam, Netherlands	BioSemi
14	g.tec nautilus	64	500 Hz	Yes (Bluetooth)	10 hours	360g	No	$$	1999	AUSTRIA	g tec
15	Cognionics Mobile 64/128	64/28	500-1000Hz	Yes (Bluetooth)	6 hours Bluetooth / 10 hours SD card	250g	No	$$	2010	San Diego	CGX
16	Cognionics Quick 8/20/30	8/20/30	250/500/1,000/2,000	Yes (Bluetooth)	10 hours wireless and 12 hours	450 g	No	$$	2010	San Diego	CGX
17	mBrainTrain Smarting	24	250-500 Hz	Yes (Bluetooth)	5 hours	60 g	No	$$	2012	Oldenburg	mBrainTrain
19	NeuroSky	Single	512 Hz	Yes (Bluetooth)	AAA battery with 8 hours of battery life	14.4 g	Yes	$99.99	2004	US-Silicon Valley	NeuroSky

20	**Muse**	**7 finely calibrated sensors**		**Wireless Connection: BT 4.0**	**5 hours**	**NA**	**NA**	**$199.00**	**2014**	**Toronto**	**Muse**