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<u>Methods of Seizure Detection: A Literature Review</u>

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Abstract:

An epileptic seizure is a neurological disorder caused by abnormal activity of nerve cells in the brain. Epileptic seizures may happen while the patient is awake or asleep, and may cause loss of consciousness, falling, or massive muscle spasms. Frequent seizure events are dangerous as it can cause extreme injury and even death. Since the period of most seizures is less than two minutes, it is impossible to directly monitor all patients at risk of seizure. Devices have been developed such as electroencephalogram (EEG), and mattress pressure sensors to detect seizures and alert caregivers. Despite all the benefits of these systems, these systems cannot accurately detect seizures. EEG and ECG are impractical and not suitable for long term seizure detection and mattress pressure sensors do not allow for accurate detection in all patients as a weight threshold must be reached for the sensors to detect movement. To address this researchers have developed wearable devices that combine ECG and Photoplethysmography (PPG) to monitor and detect seizure events [1]. PPG is an optical technique that uses a light source and a photodetector at the surface of the skin to measure the volumetric changes in blood circulation which allows for the detection of heart rate [2]. PPG is also being combined with wearable devices and video to allow for an innovative seizure detection system. In this literature review, traditional methods of seizure detection such as EEG, mattress pressure sensors, video-based detection, and integrating PPG with wearable devices to detect seizures will be discussed and compared to understand and further appreciate seizure detection systems.

Introduction:

Seizures are one of the leading brain diseases that do not have a cure. Seizures can happen to all individuals of varying ages from infants to adults, and they're currently is not a consistent detection system. Throughout the year's researchers have developed detection systems to detect when the individual will have a seizure allowing for an alert system. These alert systems are important as they allow for the individual to seek a safe place. The individual must seek a safe environment as once the seizure begins the individual has no control over their body. The seizure events can result in uncontrollable repetitive motion, shaking, and falling. This is especially dangerous if the seizure is about to occur and the individual is driving or eating. There must be a discussion of the current seizure detection systems out there and future applications of detection systems.

Methods and Results:

EEG:

Epilepsy is one of the most common neurological disorders and detection is crucial for treatment. Epileptic seizures occur at any time and can be fatal as the person loses all consciousness at any moment. Unfortunately this disease has no treatment, however advanced diagnosing allows for the improved medication and improved quality of life for these patients. EEG is one of the oldest detection systems for seizures. EEG works by measuring voltage changes between electrodes placed along the subject's scalp that measure current flow through neurons in the brain. From this doctors are able to detect abnormal brain activity and further make diagnosis. Before discussing current methods that use EEG for detection of seizures, it is important to discuss how EEG works and its applications for a myriad of brain disorders.

When an EEG exam is ordered the patient is required to have electrodes placed on the surface of their scalp. The electrodes measure the absolute electrical potential generated by the neurons on the underneath the cerebral cortex[4]. EEG measures pyramidal cells or pyramidal neurons which are primarily located in layer 3 and layer 4 of the cerebral cortex, these cells transform synaptic input into action potential. There are both excitatory and inhibitory action potentials (EPSPs/ IPSPs). Excitatory action potentials are generated after neuronal depolarization and inhibitory action potentials are generated after hyperpolarization. The summation of these excitatory and inhibitory action potentials creates an electrical field with positive and negative dipoles, and these dipoles are parallel to the pyramidal cells. EEG measures the summation of these signals [4].

Although EEG is known for its use in detection of epileptic seizures, and is also used for classifying and localizing the onset of a seizure. Localized seizures also known as focal seizures, which are seizures that arise from abnormal neuronal activity from a localized area of the brain [5]. EEG can also be used for diagnosing brain tumors, brain damage (from injuries), inflammation of the brain, stroke sleep disorders. Interestingly, EEG can also be used for anesthetic procedures to monitor the depth of anesthesia during vascular surgery [6].

Although there are benefits of using EEG for seizures, there are some challenges. It has been found that EEG of patients with epileptic seizures and those with not have some overlap of patterns in the EEG signal [4]. This causes problems as there needs to be a distinct difference between a healthy patient and non-healthy for diagnosis, so if we do not have this it causes ambiguity in diagnosis and requires further diagnostic exams. The other limitation of using EEG, is that an expert is needed to analyze the chart. This is very time-consuming and a human might have misdiagnosis.

To address some of EEG's limitations researchers are using machine learning methods such as computational neural networks to detect seizure events instead of manual feature extraction. In the study, a convolutional neural network based on raw EEG data instead of feature extraction was used to distinguish ictal, preictal, and interictal segments for epileptic seizure in a total of 21 patients with medically intractable focal epilepsy. The database was retrieved from Physionet called CHB-MIT and another called Frieburg database was obtained from hospital data in Germany [16]. Preictal is before the onset of seizure, ictal is during seizure onset, and interictal is defined as period between a seizure. There were a total of three types of experiments which involved binary classification (experiment 1: preictal vs interictal) and (experiment 2: interictal vs ictal), and the third experiment which was interictal vs ictal vs preictal. Using frequency domain signals for the Frieburg database the accuracy for the first experiment was 96.7%, the accuracy for the second experiment was 95.4% and the accuracy for the last experiment was 92.3%[16] . Using time domain signals for the Frieburg database the accuracy for the first experiment was 91.1%, the accuracy for the second experiment was 83.8% and the accuracy for the last experiment was 85.1%[16]. Using the CHB-MIT for the frequency domain database the accuracy for the first experiment was 95.6%, the accuracy for the second experiment was 97.5% and the accuracy for the last experiment was 93% [16]. Using the CHB-MIT database for the time domain the accuracy for the first experiment was 59.5%, the accuracy for the second experiment was 62.3% and the accuracy for the last experiment was 47.9% [16].The results are shown in the table 1 below.

Patient ID	Binary Case						Interictal vs. Ictal vs. Preictal
	Interictal vs. Preictal			Interictal vs. Ictal			
	acc	sen	spe	acc	sen	spe	acc
1	0.967	0.960	0.973	0.960	0.940	0.980	0.930
2	0.997	0.997	0.997	0.975	0.957	0.993	0.963
3	0.945	0.960	0.930	0.945	0.933	0.957	0.928
4	0.995	1.000	0.990	0.992	0.997	0.987	0.986
5	0.982	0.983	0.980	0.988	0.987	0.990	0.971
6	0.995	1.000	0.990	0.988	0.997	0.980	0.911
7	0.980	0.987	0.973	0.968	0.943	0.993	0.937
8	0.815	0.833	0.797	0.755	0.743	0.767	0.678
9	1.000	1.000	1.000	1.000	1.000	1.000	0.913
10	0.992	0.987	0.997	0.967	0.943	0.990	0.967
11	1.000	1.000	1.000	0.973	0.947	1.000	0.963
12	0.993	0.987	1.000	0.987	0.973	1.000	0.986
13	1.000	1.000	1.000	0.970	0.957	0.983	0.896
14	1.000	1.000	1.000	0.998	0.997	1.000	0.954
15	0.958	0.953	0.963	0.902	0.857	0.947	0.856
16	0.868	0.860	0.877	0.907	0.860	0.953	0.867
17	0.958	0.943	0.973	0.987	0.983	0.990	0.956
18	0.943	0.927	0.960	0.920	0.890	0.950	0.914
19	0.965	0.963	0.967	0.948	0.903	0.993	0.960
20	0.960	0.960	0.960	0.925	0.870	0.980	0.920
21	1.000	1.000	1.000	0.985	0.990	0.980	0.933
Avg	0.967	0.967	0.968	0.954	0.937	0.972	0.923

Table 1: Frequency domain signal results for all patients in the Freiburg database [16]. Granted permission from Frontiers in Neuroscience through Creative Commons. No change was made to the figure.

Overall in both databases the network was able to more accurately identify seizure in frequency domain. This tells us that the frequency domain is more accurate in detection of seizure events in comparison to time domain. One limitation of using convolutional neural networks is the need for large volumes of data, and in this study large volumes of continuous EEG recordings for deep learning. Another thing that was not mentioned is the variation in the patients, and how that can affect the results. There are different regions in the brain where the seizures occur for each subject, the patients vary depending on age, their sexes and more. This should be investigated in further studies, for example maybe building a network around the individuals physical characteristics might result in higher accuracy.

In another study similar to Zhou et al (2018) , researchers focused on two different databases to build their neural network to detect seizures: CHB-MIT, and EPILESPIAE. The results showed an average accuracy and specificity values of 99.3% and 99.6%, respectively, for the CHB-MIT dataset, and corresponding values of 98.0% and 98.3% for the EPILEPSIAE patients. Although the researchers focused only on feature domain extraction, the study tells us that there is high accuracy and specificity with neural networks. In the future, physicians can rely entirely on detecting seizures with computers, or can rely on computers to confirm diagnosis.

The limitations in this study as with any deep learning is the computational cost to run these programs especially during the training phase. Nonetheless deep learning provides a promising future for seizure detection.

Mattress Pressure Sensors:

For patients that are not hospital bound there is a need for constant monitoring of seizure events, especially those that occur at night away from caretakers. The development of mattress pressure sensors allows for caretakers to not monitor the patient throughout the night, and instead get notified by the pressure sensors on the patient's mattress. Electromechanical film also known as Emfit® , is a mattress pressure sensor that is triggered by rhythmic motor activity of specific frequency, duration and intensity. The way that the mattress pressure sensor works is through ballistography (BCG), which is a technique that produces graphical representation of movement through the ejection of blood into the vessels with each heartbeat [7]. In other words heart beats can be induced through repeated motion, and ballistography can measure the mass movements through the measurements of the mass of circulating blood and the heart during the cardiac cycle [7]. During atrial systole, when blood is pumped through large vessels in the heart the center mass of the body moves towards the head of the body, however when the blood is moving toward the peripheral vessels, the center mass of the body is toward the feet. The shifting of the center of mass contributes to the ballistography waveform because blood distribution changes [7]. Figure 1 below [9] shows an example of a typical BCG waveform.

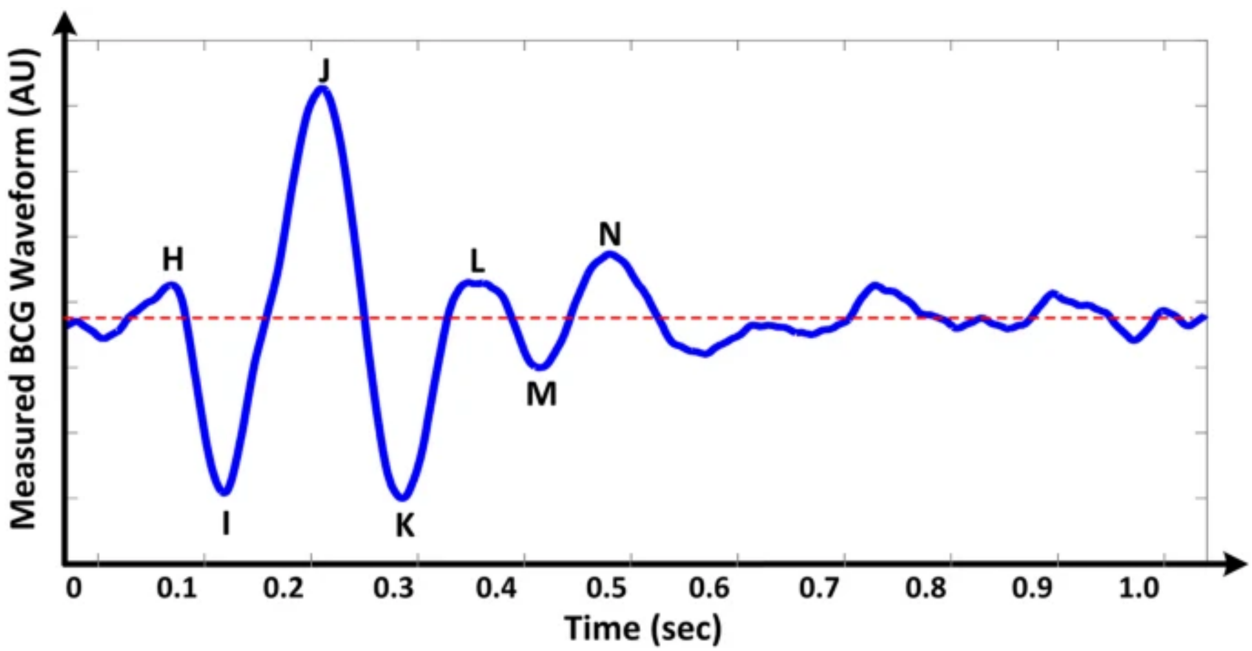


Figure 1: Example BCG waveform [17]. No changes were made to the original figure. Permission granted by Scientific Reports through Creative Commons License.

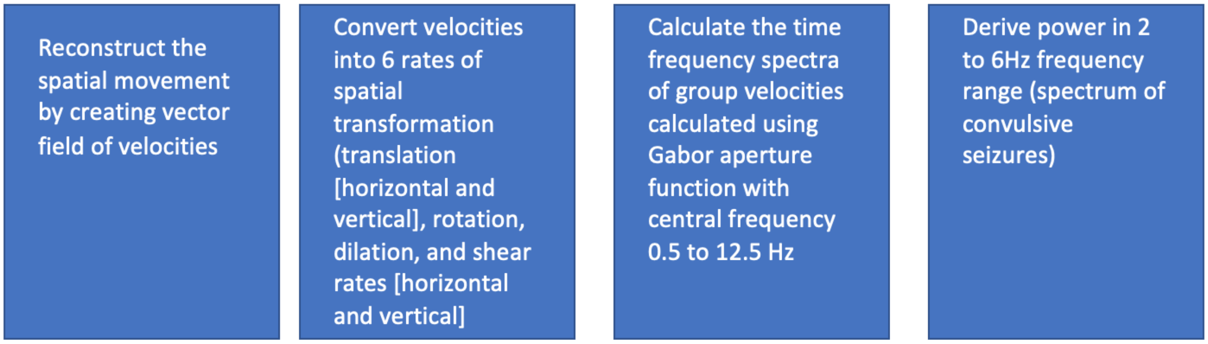
Most devices today that measure acceleration BCG, as the sensors measure the force (mass * acceleration). The extrema of the BCG waveform is labeled as H, I, J, K, L, M, N. The H phase refers to pre-ejection, the I,J,K section refers to ejection, and the L,M,N section refers to diastolic [8].

Researchers wanted to assess the specificity and sensitivity of Emfit® in the adult patient population by comparing it with the gold-standard of seizure detection video-EEG (vEEG) monitoring [10]. Seventy-nine patients were recruited over a 15 month period, and the sensors were placed under the mattress for and was repeated for each new patient. If a patient exerted force on the mattress, the mattress sensor would detect this force and report the force as a voltage. The monitor reports a signal based on the frequency, intensity and duration of force applied to mattress sensors. Each patient also had a corresponding video-EEG recorded, so that the Emfit data and the vEEG were compared. Of the 79 patients, 51 patient's data was analyzed, the remaining 28 were excluded due to experimental issues such as faulty set up. The results showed that out of the 3741 hours of vEEG recording, there were a total of 132 events that resulted in Emfit activation. These included 16 true positives, 93 true negatives, 21 false positives, and 2 false negatives. The subgroup of nocturnal events included 8 true positives and 20 true negatives. Since the data showed no false positive this makes the device 100% sensitive and specific to generalized convulsions that occur during sleep [10]. The researchers also noted that there was no statistically significant difference in the detection rate of generalized convulsions during day and night hours.

One limitation of the study is that the researchers did not mention how the sensitivity of the pressure sensors varies for different weight thresholds. The reason mattress pressure sensors are not a universal solution for seizure detection is because there needs to be a certain threshold to detect the movements. For patients that do not reach the threshold there would be a lower sensitivity. This is why infants often do not have pressure sensors to detect seizures and often rely on EEG for the detection and diagnosis of seizures. Further studies should evaluate how the pressure sensors can be adjusted to increase the sensitivity for infants.

Video-based detection:

With the era of technology and improved video quality, the development of video-based detection has allowed for both in-home and hospitals to use video to detect seizures without the need for pressure sensors, wearable devices or EEG. Researchers investigated the detection of seizures using real-time video-detection of nocturnal convulsive seizures. The researchers created an algorithm that calculates the relative frequency content based on group velocity reconstruction from video-sequence optical flow. The researchers used the algorithm on 22 children between ages of 3 to 17 years old. The algorithm was applied at home or in a residential care setting. The algorithm focuses on detecting specific patterns of convulsion that is indicative of seizures, and if the output signal exceeds a previously defined threshold then an alarm is set. A flow diagram below shows the steps of how the video is continuously being processed.



If the output signal is greater than previously determined threshold of 0.51 for greater than 4 seconds an alarm occurs.
Figure 2: flow diagram of the video-based detection algorithm

The researchers validated the algorithm with long-term night videos of children with refractory epilepsy. The algorithm was able to detect 118 out of the 125 seizure events, with a total of 81 false alarms in six children [10]. The researchers claim that the false alarms were due to behavior-related movements of the child during their sleep. In conclusion the researchers confidently claim that the non-contact video-based detection algorithm is able to detect reliably nocturnal epileptic seizures with a limited number of false alarms.

One of the concerns of video-based detection is whether the algorithm is able to work on individuals of darker skin tones. There was no mention of this in the paper, however this is a universal problem with video-based detection algorithms. Another thing that the paper failed to mention is the age range for the exclusion criteria of the patients. The patients were between 3-11 years old, the question arises whether similar results would be seen in another age group. One other concern is whether similar results would be seen in another category of seizures as the study focused on nocturnal convulsive seizures.

In another paper researchers investigated video-based detection algorithms but integrated deep learning. Deep learning is a subfield of machine learning that focuses on using multiple layers to extract higher-level features from raw data. Deep learning is very beneficial in the field of medicine as it allows computers to make predictions and even diagnose diseases. Yang et al (2021) wanted to improve upon video-based detection by integrating deep learning. The researchers state that most video-detection systems rely on hand-designed features, and by using deep learning we can avoid having to rely on manual feature detection. In the study the researchers identified 76 generalized tonic clonic seizures (GTCS) from 37 patients who all underwent long-term video EEG monitoring as well as interictal video data from the same patients, and 10 full night seizure-free recordings. The researchers were able to evaluate the performance of the algorithm based on individual video-frames (convolutional neural networks-CNN) or video sequences (CNN and long-short term memory networks-LSTM). The researchers found that by combining CNN and LSTM the video based detection system performed better with a mean sensitivity of 88% for each individual and a 92% mean sensitivity across all the patients [11]. The figure below illustrates the results for sensitivity, specificity, number of seizures, and total time of video data for all 37 patients.

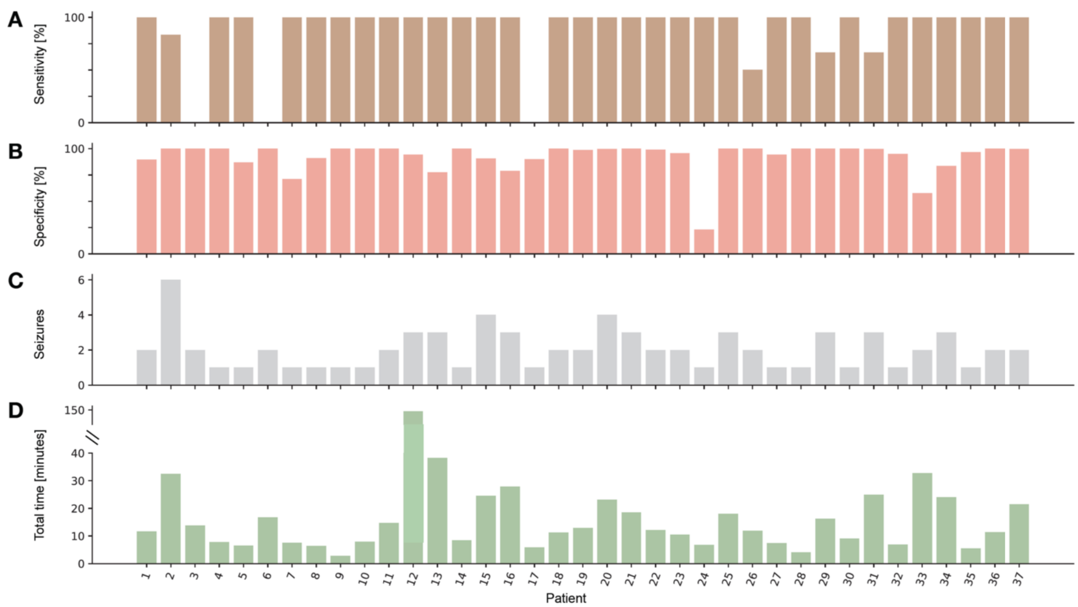


Figure 2: Detection performance results. A, Sensitivity. B, Specificity. C, Number of seizures for each patient. D, Total duration of video data for each patient [11]. Permission granted for use by IEEE Journal of Biomedical Health Informatics. No changes made to the original figure.

One concern of the detection system is similar results would be seen in other categories of seizures. The researchers did state that they focused on GTCS as it is the most common occurrence seen in patients. The researchers also state that GTCS is most favorable for video-based detection due to their characteristic motor movements that video-based algorithms can pick up. In either case further studies should focus on finding performance of the video-based algorithm for different seizures as a video-based detection system as there is so much data out there deep learning is becoming integrated in many algorithms for disease detection.

<u>Photoplethysmography and wearable devices:</u>

Before discussing photoplethysmography in combination with wearable devices to detect seizure events there needs to be a discussion on how photoplethysmography (PPG) works. Photplethysmography, also known as pulse oximeter waveform, is amplified by light absorption by local tissue over time [12]. PPG uses infrared light to measure volumetric blood circulation in localized tissue. Most devices such as the Apple Watch use PPG to detect heart rate. Typically these devices have a light source and a photodetector. The light source emits the infrared light to the surface of the tissue and the photodetector measures the reflected light from the tissue [13]. The reflected light is proportional to the blood volume variations [14]. The reason this works is because arteries are able to absorb light better than surrounding tissues. Naturally as the arteries contract in each heartbeat and heart pressure , the intensity of the absorbed light rises and falls and PPG is able to detect the changes in the absorbed light. The figure 3 below illustrates how PPG works. On the top is low pressure from the arteries, which means that more of the light will be reflected, on the bottom there is greater pressure from the arteries which means that less light will be reflected.

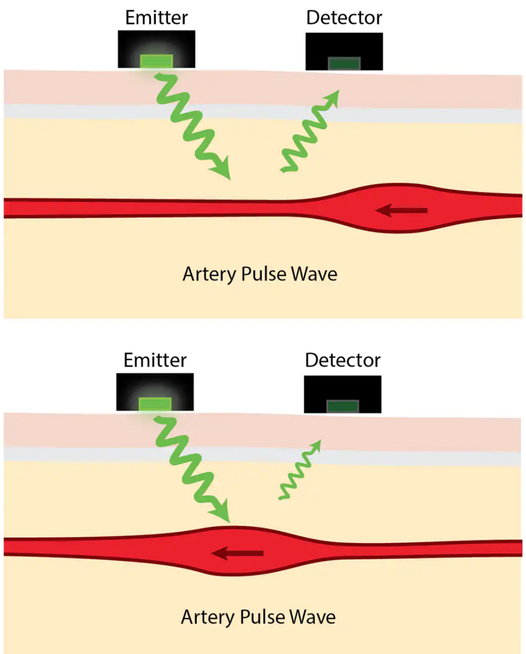


Figure 3: Illustration of how the photodetectors receive light from the emitter with varying arterial pressure [14]. No changes were made to the figure.

To compare PPG with traditional methods of seizure detection, researchers have developed two wearable devices, one based on ECG and the other based on PPG and compared the sensitivity of the wearable devices with only ECG which is used and referred to as the "hospital system". The algorithm of the wearable devices classified the seizures based on the heart rate features. There were 11 patients total with temporal lobe epilepsies. It was found that the sensitivities of the hospital system, the wearable ECG device, and the wearable PPG device were respectively 57%, 70%, and 32% [1]. It was also found that the false-alarms per hour were 1.92 for hospital systems, 2.11 for wearable ECG, and 1.80 for wearable PPG.

The authors mentioned that they focused the study on temporal lobe epilepsies as those have significant autonomic nervous system changes especially in the cardiovascular. Figure below shows the significant heart rate changes for patient 4 during the seizure event.

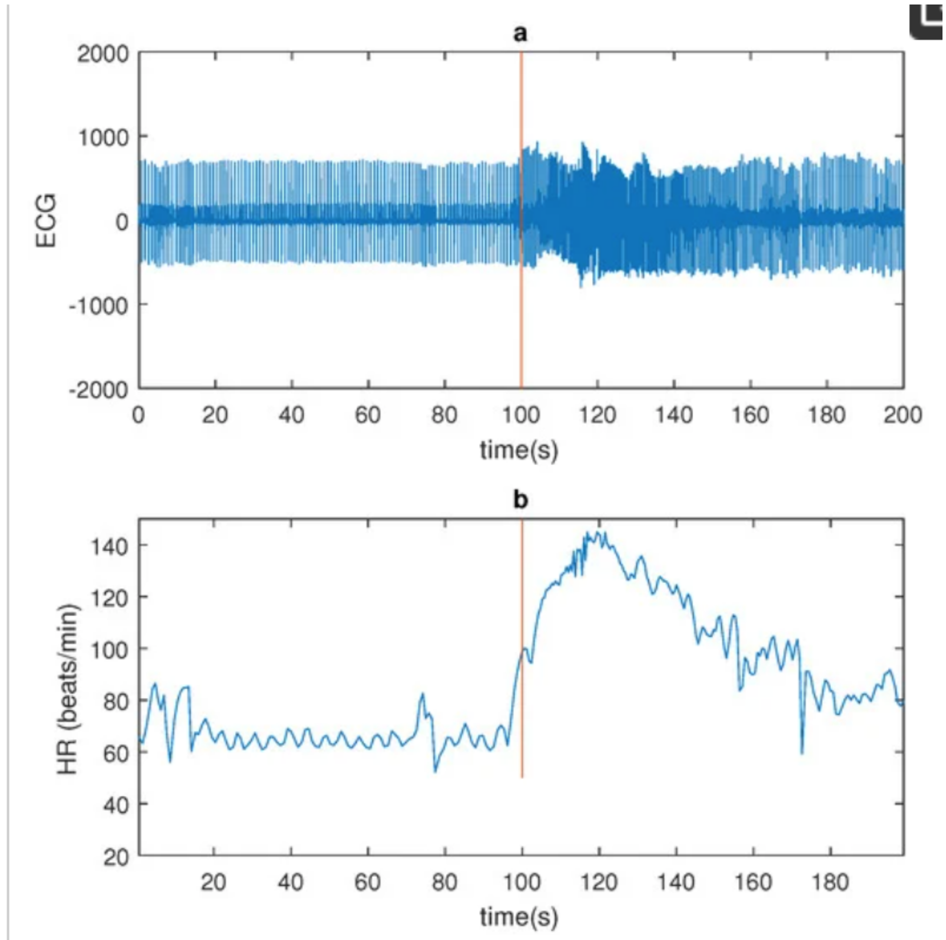


Figure 4: Example of seizure patient 4 [1], no changes were made to the figure. Permission for use granted by MDPI Open Access License.

It is clear from the low sensitivity of PPG, that the ECG wearable device and the hospital system performed much better. The low sensitivity of the PPG according to the authors is based on motion artifacts and claim that 55% of seizures could not be detected due to the interference from motion. This is the limitation of PPG that was mentioned earlier, during activity there may be movement and the sensors are not stable in their position. The authors found this limitation in their study with a low sensitivity of the PPG wearable device. The placement of the device was on the dominant hand on the wrist, which is subject to a lot of motion. Further studies need to be done to investigate the placement of the device on an area that is not subject to too much motion. Overall, the study showed that the ECG systems are far superior to PPG, and resulted in greater sensitivity.

In another study, researchers analyzed PPG signals from patients with generalized tonic seizures. There were a total of 174 patients. The patients were required to wear PPG devices on their wrist or ankle during EEG long-term monitoring. The researchers analyzed three time periods, baseline, pre seizure, and post seizure. Baseline is defined 30 minutes before a seizure event, pre seizure is a few minutes before and post-seizure is after a seizure event. The researchers observed an increase in the PPG frequency pre- and post seizure periods. There was a 0.22Hz increase in pre seizure and 0.58Hz post seizure, as a baseline seizure-free frequency was found to be 0.05 Hz [3].

Although the study did not focus on the detection of the seizure events, this study is important for understanding how we can use PPG as a biomarker for seizure events. There is still not a solid system that detects seizures before an event. The results in this paper indicate that PPG is a promising biomarker and further studies could investigate how increased frequency in PPG can be indicative of a seizure and help alarm patients before a seizure event occurs. This would help patients tremendously, as most detection systems only detect seizures during an event, by having a system alert patients before a seizure event, the patient has a higher chance of seeking a safe place before the seizure onset.

Discussion:

When comparing the seizure detection systems mentioned above it is clear that some systems are more convenient than others. The EEG system is ideal if there is an expert that can read the scans and if a seizure event occurs during the time of the test. It is not convenient in areas that do not have the system such as a patient's home. It is also very uncomfortable for the patient to wear for long periods of time. There is then a move toward video detection systems, these systems can detect seizure events from video and can alert care takers that the individual is having a seizure in real time. This is far superior in comparison to the EEG system as there is no need for an expert to watch the videos, instead the system itself can detect the seizure events. The video detection systems have become far more superior with the incorporation of data mining algorithms such as neural networks that can use a patient's data and create better detection systems. However, there are limitations with the video detection systems in infants and individuals with darker pigmentation. Oftentimes the infants do not have a large surface area for the video to pick up the variations in the heart beat to detect a seizure. For individuals with darker pigmentation there needs to be higher levels of light brightness for the video to detect face. Video detection does offer a solution to the uncomfortable EEG electrodes, but may not be ideal for overnight detection. There is then the move toward mattress pressure sensors, these sensors are placed underneath the mattress of the patient, and detects seizures with movement. This has allowed for a detection of seizures overnight, however not all seizures result in repetitive movement that the mattress pressure sensors need to detect the seizures. This has allowed for the creation of wearable devices that detect seizures, these wearable devices have PPG integrated in them that detect heart rate. The variations in the heart rate can be detected from the device as a seizure event and alert the patient. However, PPG uses a light source and this light source often does not penetrate as deep in individuals with darker pigmentation.

Conclusion:

Overall, the seizure detection systems mentioned above have their benefits some more convenient than others. It is important that there are improvements to the seizure detection system. It is necessary there be a detection system for all individuals no matter the age, skin color and type of seizure. Detection systems are incredibly important for these patients to seek a safety place before the seizure onset. This is also crucial because there is currently not a system out there that can detect seizures before an event. Although PPG is a promising biomarker, there is hope that further applications could investigate PPG in detecting seizure events before they occur.

References:

[1] Vandecasteele, Kaat, Thomas De Cooman, Ying Gu, Evy Cleeren, Kasper Claes, Wim Van Paesschen, Sabine Van Huffel, and Borbála Hunyadi. “Automated Epileptic Seizure Detection Based on Wearable ECG and PPG in a Hospital Environment.” *Sensors (Basel, Switzerland)*17, no. 10 (October 13, 2017). https://doi.org/10.3390/s17102338.

[2] Castaneda, Denisse, Aibhlin Esparza, Mohammad Ghamari, Cinna Soltanpur, and Homer Nazeran. “A Review on Wearable Photoplethysmography Sensors and Their Potential Future Applications in Health Care.” *International Journal of Biosensors & Bioelectronics*4, no. 4 (2018): 195–202. https://doi.org/10.15406/ijbsbe.2018.04.00125.

[3]: Mohammadpour Touserkani, Fatemeh, Eleonora Tamilia, Francesca Coughlin, Sarah Hammond, Rima El Atrache, Michele Jackson, Megan Bendsen-Jensen, et al. “Photoplethysmographic Evaluation of Generalized Tonic-Clonic Seizures.” *Epilepsia* 61, no. 8 (August 2020): 1606–16. https://doi.org/10.1111/epi.16590.

[4]: Xun, Guangxu, Xiaowei Jia, and Aidong Zhang. “Detecting Epileptic Seizures with Electroencephalogram via a Context-Learning Model.” *BMC Medical Informatics and Decision Making* 16, no. Suppl 2 (July 21, 2016). https://doi.org/10.1186/s12911-016-0310-7.

[5]:Ramakrishnan, Sharanya, and Appaji Rayi. “EEG Localization Related Epilepsies.” In *StatPearls*. Treasure Island (FL): StatPearls Publishing, 2021. http://www.ncbi.nlm.nih.gov/books/NBK557645/.

[6]: Zhang, X.-S., R. J. Roy, and E. W. Jensen. “EEG Complexity as a Measure of Depth of Anesthesia for Patients.” *IEEE Transactions on Biomedical Engineering* 48, no. 12 (December 2001): 1424–33. https://doi.org/10.1109/10.966601.

[7]: “Ballistocardiogram Signal Processing: A Review | SpringerLink.” Accessed April 18, 2021. https://link.springer.com/article/10.1007/s13755-019-0071-7.

[8]:“Ballistocardiogram (BCG).” Accessed April 18, 2021. http://www.cs.tut.fi/sgn/SSSAG/BCG.htm.

[9]: Kim, Chang-Sei, Stephanie L. Ober, M. Sean McMurtry, Barry A. Finegan, Omer T. Inan, Ramakrishna Mukkamala, and Jin-Oh Hahn. “Ballistocardiogram: Mechanism and Potential for Unobtrusive Cardiovascular Health Monitoring.” *Scientific Reports* 6, no. 1 (August 9, 2016): 31297. https://doi.org/10.1038/srep31297. (image BCG)

[10]:Narechania, A. P., Garić, I. I., Sen-Gupta, I., Macken, M. P., Gerard, E. E., & Schuele, S. U. (2013). *Assessment of a quasi-piezoelectric mattress monitor as a detection system for generalized convulsions. Epilepsy & Behavior, 28(2), 172–176.* doi:10.1016/j.yebeh.2013.04.017

[11]:Yang Y, Sarkis R, El Atrache R, Loddenkemper T, Meisel C. Video-based Detection of Generalized Tonic-clonic Seizures Using Deep Learning. IEEE J Biomed Health Inform. 2021 Jan 6;PP. doi: 10.1109/JBHI.2021.3049649. Epub ahead of print. PMID: 33406048.

[12]: Alian, Aymen A., and Kirk H. Shelley. “Photoplethysmography.” *Best Practice & Research Clinical Anaesthesiology*, Hemodynamic Monitoring Devices, 28, no. 4 (December 1, 2014): 395–406. https://doi.org/10.1016/j.bpa.2014.08.006.

[12]: Castaneda, Denisse, Aibhlin Esparza, Mohammad Ghamari, Cinna Soltanpur, and Homer Nazeran. “A Review on Wearable Photoplethysmography Sensors and Their Potential Future Applications in Health Care.” *International Journal of Biosensors & Bioelectronics* 4, no. 4 (2018): 195–202. https://doi.org/10.15406/ijbsbe.2018.04.00125.
[13]: Wang C, Li Z, Wei X. Monitoring heart and respiratory rates at radial artery based on PPG. *Opt Int J Light Electron Opt* 2013;124(4):3954–3956.
[14]:Woolley, Sandra, and Tim Collins. “Some Heart-Rate Monitors Give Less Reliable Readings for People of Colour.” The Conversation. Accessed April 18, 2021. http://theconversation.com/some-heart-rate-monitors-give-less-reliable-readings-for-people-of-colour-121007.
[15]:(Zhou, M., Tian, C., Cao, R., Wang, B., Niu, Y., Hu, T., Guo, H., & Xiang, J. (2018). Epileptic Seizure Detection Based on EEG Signals and CNN. *Frontiers in neuroinformatics*, *12*, 95. https://doi.org/10.3389/fninf.2018.00095)
[16]: “Automatic Seizure Detection Based on Imaged-EEG Signals through Fully Convolutional Networks | Scientific Reports.” Accessed April 18, 2021. https://www.nature.com/articles/s41598-020-78784-3.
[17] Kim, Chang-Sei, Stephanie L. Ober, M. Sean McMurtry, Barry A. Finegan, Omer T. Inan, Ramakrishna Mukkamala, and Jin-Oh Hahn. “Ballistocardiogram: Mechanism and Potential for Unobtrusive Cardiovascular Health Monitoring.” *Scientific Reports* 6, no. 1 (August 9, 2016): 31297. https://doi.org/10.1038/srep31297