IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 5, Issue 3, March 2016

Epilepsy seizure detection using EEG - Curvelet feature selection and SVM classification

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Abstract: According to World Health Organization (WHO), epilepsy is one of the most common primary diseases of the central nervous system worldwide, which is aggravated by the sudden factor that characterizes the occurrence of an epileptic event. Thus, the ability to detect episode before its onset appears as a mitigating factor to the unpleasant effects arising from this situation. In this paper, already implemented to detect epilepsy by using WiSARD neural network classification through this multiple evaluation had been processed. seizure detection, the WiSARD weightless neural network was explored.We proposed in this project to get high accuracy first collect the features of seizures in EEG signal through DWT co-efficient analysis. And then parameters evaluated continuously in multiple level of wavelet, passed the features to SVM classifier giving effective result compare to existing one.

Index Terms: Support vector machine(SVM), Discrete Wavelet Transform(DWT), WiSARD, Electroencephalogram (EEG).

I. INTRODUCTION

In the UK, there are over 6 lakh cases of epilepsy. About 2% of the population worldwide (60 million approx) have epilepsy, and nearly 75% of the cases take place in developing countries. Epilepsy cannot be cured, but epilepsy seizure is surely controllable with medication in about 70% of total epilepsy cases. However in those whose seizures do not respond to medication, surgery, n euro stimulation or changes related to diet may be considered.Electrical activity is taking place in our brain all the time. A seizure results of an impulsive burst of intense electrical activity. This activity causes a temporary disturbance to the normal working of brain, meaning that the brain's messages getting mixed up thus result in an epileptic seizure.Doctors, Scientists and researchers used a technique called electroencephalography (EEG) to examine the brain signals.

Epilepsy is a chronic neurological disorder that affects more than 50 million people worldwide (prevalence between 5-10 per 1000 people.It is characterized by recurrent unprovoked events, called seizures, which are symptomatic of abnormal brain activity. There are many different epilepsy syndromes and seizure types; ranging from mild, hardly noticeable to severe, life threatening seizures. Prescription of pharmaceuticals (antiepileptics) is the primary treatment by which seizures are successfully suppressed in the majority of patients. Approximately 30% of the epilepsy patient population has refractory epilepsy; they still suffer from seizures despite receiving the best possible treatment. To improve the quality of care and diagnosis, long-term electroencephalogram (EEG) monitoring is frequently performed. It consists in placing up to 100 gel electrodes on the scalp. Nevertheless EEG monitoring is not well-suited for monitoring patients in their daily-life activities. The location and the multitude of electrodes wires make it cumbersome and uncomfortable to wear. Such monitoring systems are also difficult to set up as it requires highly trained (expensive) personnel. Moreover, the analysis of the huge amount of data is laborious. Recently, wireless ambulatory EEG devices for long term epilepsy monitoring and real-time seizure detection have been developed [Casson, 2009; Raghunathan, 2009; Waterhouse, 2003; Patel, 2009]. However, the current ambulatory EEG systems encounter several limitations, such as device size,weight, and unreliable electrodes attachment to scalp [Casson, 2008]. Because the electrodes are placed on the head, this may also not be socially accepted for dailylife use. Having an online continuous seizure detector packaged in a comfortable, unobtrusive and wearable device would allow not only improve the quality of care by providing a long-term diagnosis to clinicians. It would also enhance patient‟s safety by triggering alarm notifications in case of major life-threatening seizures during daily-life activities.

The challenging issue of detecting epileptic seizures in real-time while not impairing patient‟s daily-life calls for alternative ways of detection. The seizures express themselves in various physiological changes, relating to the activated part of the brain and the level of excitation of the seizure. Amongst these, cardiac abnormalities such as, ST-depression, T-wave inversion [Opherk, 2002] or the most common one, changes in the heart rhythm (sinus tachychardia or bradycardia), have been reported in several studies [Blumhardt, 1986;Epstein, 1992;Zijlmans, 2002; Opherk, 2002; Leutmezer, 2003]. The focus of the current study is to detect heart-rate (HR) changes related to epileptic seizures in real-time using a wearable cardiac monitor.

There is a need for a wireless and wearable device to allow long-term ambulatory monitoring of electroencephalogram (EEGs), where brain’s electrical activity is measured with electrodes placed on the skull. Continuously worn, EEG based, brain-computer interfaces (BCIs) could be used by paralyzed patients to control an external device with visually evoked potentials, which are EEG oscillations, with the same frequency as a flashing visual stimulus. EEG based BCI could be used for mental-work load detection to alert distracted or drowsy car drivers. Furthermore, there is a clinical need for continuos EEG monitoring to alert the patient and healthcare providers during the onset of an epileptic seizure

This paper is organized as follows. First, the requirements from the clinical field are described. Then, the low-power and miniaturized prototype is detailed as well as the embedded algorithms required to perform epileptic seizure detection. The wireless communication services which ensure reliable epilepsy-related event transmission are also presented along with the software architecture. Additionally, the epilepsy detector is characterized in terms of memory footprint, power consumption, and real-time functionality. Finally, the results of the data collection performed on healthy volunteers and epilepsy patient with the system are also provided.

The clinical gold standard for epilepsy diagnostics requires simultaneous video and electroencephalography inpatient monitoring. EEG ambulatory monitoring of outpatients has been regarded as an alternative for the time consuming and expensive current approach. EEG ambulatory monitoring also seems to be a promising tool to improve diagnosis, classification and medication prescription in patients with epilepsy and other paroxysmal diseases. Although many platforms have been trying to accomplish the outpatient monitoring, some features required for an effective ambulatory system remain to be met. Those features are descrived by the American Clinical Neurophysiology Society in their guidelines for systems of EEG long-term monitoring in epilepsy patients, and can be resumed into devices with the minimum number of channels between 32 and 64 to get a good spatial resolution and a minimum monitoring time of 24 hours running. They also recommend the usage of event detection algorithms to improve the efficiency level of these applications. The electroencephalography (EEG) acquisition platforms have been described as typical wired systems characterized by a different number of channels, sampling frequencies per channel and by the fact that the signal processing is associated with another computing device to which it connects.

The system described in this study meets the necessary specifications for long-term monitoring in both ambulatory outpatient and inpatient settings of epileptic patients. Two operation modes are supported, with differentiated power consumptions: data streaming mode (more suitable for inpatient monitoring) and event detection mode.

Epilepsy is a chronic neurological disorder affecting more than 50 million people worldwide. Epilepsy is characterized by sudden bursts of excessive electrical discharges in the brain . Such abnormal firings, called seizures, often occur without warning and for no apparent reason. The unpredictable nature of seizure occurrences poses a challenge to the diagnosis of epilepsy, as well as causes a substantial burden to the physical, social and psychological states of a patient. The ability to detect and/or predict the onset of a seizure could automatically prompt immediate medical assistance and avoid seizure-related injuries. Research studies of scalp electroencephalogram (EEG) signals of epilepsy patients have shown that characteristic features that are indicative of seizure activity can be extracted from the EEG. Various automatic seizure detection/prediction algorithms using scalp EEG have been developed and have shown promising detection performance. The success of such algorithms opens up a new possibility for better epilepsy control. For example, these methods may be used to trigger a warning signal to remote healthcare providers. More interestingly, they could also be used with seizure intervention devices to proactively stop a seizure by releasing fast-acting anti-epileptic medication or by delivering electrical stimulation to specific brain regions .

In order for the seizure detection to gain clinical value in everyday epilepsy management, it is important to have a reliable way of acquiring ambulatory EEG signals from patients. With recent advances in wireless and electronics technologies, portable wireless EEG sensor units have become an increasingly viable alternative to the conventional wired system for EEG monitoring. Unlike the wired one, the wireless EEG system allows a person to move freely. A wireless EEG sensor unit is a miniaturized, battery-powered device that has the capabilities of measuring, preprocessing and streaming EEG signals wirelessly to a data server, where further analysis or long-term storage is carried out. A wireless EEG unit enables ambulatory EEG monitoring outside clinical settings while patients are freely moving around, performing their daily activities. A major limitation of a wireless EEG sensor unit is its battery-limited lifetime. For a typical EEG setup with 32 EEG electrodes sampling at 250 Hz and a resolution of 16 bits, this generates a data rate of 125 kbps. Given such a high data rate, the conventional approach of continuously streaming the entire EEG signals to the data server is generally infeasible, because wireless transmission is highly energy consuming. In, it was shown that the wireless transmitter accounts for approximately 70% of the total power consumption of a wireless EEG system.

To reduce the power consumption in wireless transmission, the amount of data that needs to be transmitted should be reduced. A possible approach is to perform local on-board processing on the raw EEG data before their transmission. Data reduction can be achieved by compressing the EEG signals prior to transmission or by transmitting only features/sections of the signals that are pertinent to seizure detection. Earlier works explored the use of compression techniques, such as Huffman coding and wavelet coefficient thresholding, on EEG signals and demonstrated a substantial data reduction of up to 90%. Other data reduction techniques, such as dynamic channel selection and discontinuous recording, have also been proposed for seizure detection applications. However, the amount of computation needed for processing the signals comes at the cost of increased power consumption by the microcontroller at the sensor side. The reduction of transmitted data may also result in a loss of signal content, which can later impact the seizure detection performance. A thorough analysis that takes into Sensors 2014, 14 2038 account the power consumption of the microcontroller and the wireless transmitter on the sensor unit and the seizure detection performance is hence crucial when developing data reduction techniques for a wireless seizure detection system. Such analysis has not been considered in previous works.

II . EXISTING SYSTEM

Information content of EEG signals is essential for detection of many problems of the brain and in connection with analysis of magnetic resonance images it forms one of the most complex diagnostic tools. To extract the most important properties of EEG observations it is necessary to use efficient mathematical tools, to enable reliable and fast enough processing of very extensive data sets in most cases. Digital filters can be used in the initial stage of EEG data processing to remove power frequency from the observed signal and to reduce its undesirable frequency components. Fig. 1 presents a sample of a selected EEG channel comparing results of its segmentation by an expert and by a selected Bayesian method detecting changes of its mean value and variation. This approach has been used in this case for a selected channel only even though further channels must be taken into account in the real case as well.

III. REVIEW OF RELATED WORKS

A Real Time Based Wireless Wearable EEG Device for Epilepsy Seizure Control"Biplav C. Biswas, Student Member, IEEE, Shailesh V. Bhalerao, Member, IEEE"This full-text paper was peer-reviewed and accepted to be presented at the IEEE ICCSP 2015 conference-There is a need for a wireless and wearable device to allow long-term ambulatory monitoring of electroencephalogram (EEG's), where brain's electrical activity is measured with electrodes placed on the skull. Continuously worn, EEG based, brain-computer interfaces (BCIs) could be used by paralyzed patients to control an external device with visually evoked potentials, which are EEG oscillations, with the same frequency as a flashing visual stimulus. EEG based BCI could be used for mental-work load detection to alert distracted or drowsy car drivers. Furthermore, there is a clinical need for continues EEG monitoring to alert the patient and health care providers during the onset of an epileptic seizure.

"Mohammad Zavid Parvez, Manoranjan Paul, "EEG Signal Classification using Frequency BandAnalysis towards Epileptic Seizure Prediction" 16th Int'I Conf. Computer and Information Technology, 8-10 March 2014, Khulna, Bangladesh."-Approximately 50 million people worldwide, that is 1% of the world' population, have epilepsy (source: World Health Organization). Epilepsy is a neurological disorder that affects people of all ages, causing recurring seizures due to abnormal electrical activity in the brain. There is no cure for epilepsy however for 70% of patients, anti-epileptic medication can control seizures.

Electroencephalography (EEG) is one of the main diagnostic tests for epilepsy. EEG is a non-invasive technique used to measure and record the electrical activity in various regions of the brain. Several electrodes are attached to the scalp and measure electrical impulses. The electrodes are connected by wires to a machine which amplifies and record the resulting patterns of electrical impulses: the electroencephalogram (EEG).

"J. Klatt, H. FeldwischDrentrup, M. Ihle, V. Navarro, M. Neufang, C. Teixeira, C. Adam, M. Valderrama, C. AlvaradoRojas, and A. Witon, "The epilepsiae database: An extensive electroencephalography database of epilepsy patients," Epilepsia, no. 53, 9, pp. 1669– 1676, 2012"-Predicting epileptic seizures would change the life of millions of people. This work presents the results of a large study involving 216 patients with long-term scalp (sEEG) and intracranial (iEEG) records. A high-dimensional features space is built using time series data of 6 channels and 22 features per channel Patient-specific predictors based on SVM are developed and evaluated in relation to sensitivity and false-prediction rate. A substantial number of seizures has been correctly predicted and a comparative study is made with relation to the choice of electrodes, localization lateralization and preictal time duration. For a set of patients the results may be considered of clinical relevance compared to an analytic random predictor.

"Y. Song, J. Crowcroft, and J. Zhang, "Automatic epileptic seizure detection in EEGs based on optimized sample entropy and extreme learning machine," J. Neurosci. Meth., vol. 210, no. 2, pp. 132-146, 2012"- Epilepsy is one of the frequent brain disorder that may consequence in the brain dysfunction and cognitive disorders. Epileptic seizures can occur due to transient and unexpected electrical interruptions of brain. EEG (ElectroEncephaloGram) is one of the non-invasive methods for analyzing the human brain dynamics that affords a direct evaluation of cortical behavior.

Seizures are featured by short and episodic neuronal synchronous discharges with considerably enlarged amplitude. This uneven synchrony may happen in the brain accordingly i.e., partial seizures visible only in few channels of the EEG signal or generalized seizures, which are seen in every channel of the EEG signal involving the whole brain. Existing analysis of epilepsy depends on difficult visual screening by extremely trained clinicians.

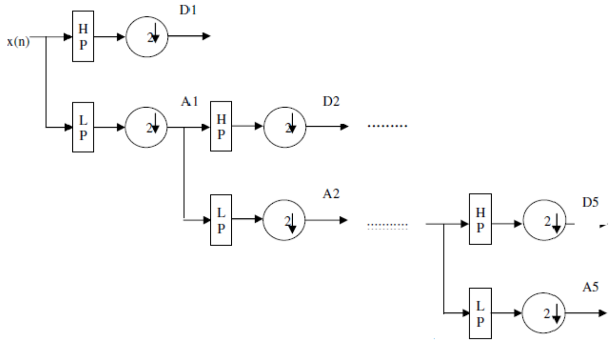
Data recordings create very lengthy data, and therefore the inspection and identification of epilepsy takes more time for diagnosis. At present time computerized systems are usually established to make the diagnosis simpler. This paper discusses an implementation of automated epileptic EEG detection system using neural networks. In this paper, a statistical parameter regarded as Sample Entropy (SampEn), is used as a method for feature extraction for performing the task of classifying EEG signals.

IV. PROPOSED SYSTEM

The EEG signal produced provides a non-invasive, high time resolution, interface to the brain, and as such the EEG is a key diagnosis tool for conditions such as epilepsy, and it is frequently used in Brain-Computer Interfaces. EEG compression is achieved by exploiting correlation (redundancy) in the source data. The compressibility of EEG depends on its amplitude distribution and its power spectrum. EEG is not usually considered sufficiently sparse in time or frequency domains for matching the recovery requirements of the clinical practice. However, filtered EEG show an amplitude distribution and a frequency spectrum largely concentrated in suitable ranges. EEG compression schemes have achieved up to 65% data reduction with lossless compression , and up to 89% data reduction when lossy compression is employed . Compressive sensing method is to make the signal transform into low dimensional measurement domain with under-sampling and it is also known as compressive sampling in the recent years [5–6]. Just as the bandwidth to the Nyquist-Shannon sampling theory, sparsity of the signal is the essential condition to Compressive Sensing . The relevance of using compressive sensing in these signals is double: On one hand it has been previously reported in that EEG signals meet the necessary requirements to ensure reconstruction after compression when projected in certain basis. Hence compressive sensing appears as a very attractive technique to reduce the power consumption and thus the size of future miniaturized EEG systems, which could be used in a variety of applications ranging from long term medical monitoring to brain computer interfaces . The concept of compressive sensing is based on the fact that there is a difference between the rate of change of a signal and the rate of information in the signal. Traditional Nyquist sampling, putting the signal into the digital domain ready for wireless transmission, is based on the former. A conventional compression algorithm would then be applied to all of these samples taken to remove any redundancy present, giving a reduced number of bits that represent the signal. Compressive sensing is a novel technique which suggests random acquisition of the non adaptive linear projection at lower than the Nyquist rate, which preserves signal structure. By using an optimization problem the signal is reconstructed. Wavelet Transform (WT) is a powerful time-frequency signal analysis tool and it is used in a wide variety of applications including signal and image coding. Wavelet Transform and Subband Coding (SBC) are closely related to each other. In fact the fast implementation of Wavelet Transforms is carried out using Subband (SB) filter banks. Due to this reason Wavelet Transform based waveform coding methods are essentially similar to the SBC based methods. Curvelet transform has undergone a major revision since its invention. The first generation curvelet transform is based on the concepts of ridgelet transform. The curve singularities have been handled by smooth partitioning of the bandpass images. In each smooth partitioned block the curve singularities can be approximated to a line singularity. A ridgelet transform is applied on these small blocks, where ridgelets can deal the line singularities effectively. To avoid blocking artifacts, the smooth partitioning is done on overlapping blocks which results in redundancy, and the whole process involves subband decomposition using wavelet transform, smooth partitioning and ridgelet analysis on each block; this process consumes more time. The implementation of second generation curvelet transform is based on the Fourier transform and is faster, less complex, and less redundant.

V. IMPLEMENTATION

Electroencephalography (EEG) is the prominent technology for identifying the brain abnormalities in many challenging applications in the field of medicine which includes Seizures, Alzheimer Disease, Coma, Brain death, Dysarthria. Paralyzed peoples are not having muscle control, in order to capture the brain signals for analyze the activity of the brain. EEG signals will be generally represented in high dimensional features space and it is very difficult to interpret. Machine learning methods are helpful for interpreting high dimensional feature sets and analyze the characteristics of brain patterns. Support Vector Machine is one of the popular Machine Learning methods for classifying EEG signals. SVM aims to maximize the margin in order to avoid the risk of over fitting data and minimize the misclassification error. In conventional methods like multilayer perceptron, complexities are controlled depends on number of features used where as in SVM complexities are independent from dimensionality. Optimization problem occurs due to conversion of data into high dimensional feature space and it can be resolved by using inner product of Kernel methods.Organization of this paper includes, a brief discussion about SVM is explained in Section 2. Section 3 deals with SVM classification for EEG signals and section 4 conclude the paper. Support Vector Machine was initiated by Vapnik and Cortes for two group classification problem. SVM is applied in many applications like EEG signal classification, cancer identification, seizure prediction, face recognition and speech disorder. In this MWT decomposition, the input signal is denoted as x(n) . The decomposed low pass filter outputs are denoted as A1, A2 , A3, A4 and A5 , and the decomposed high pass filter outputs are denoted as D1, D2 , D3, D4 and D5 . The Fig.2 shows the decomposition structure of MWT. Using this structure, the decomposition stage of EEG signal is calculated.



Decomposition of MWT

IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

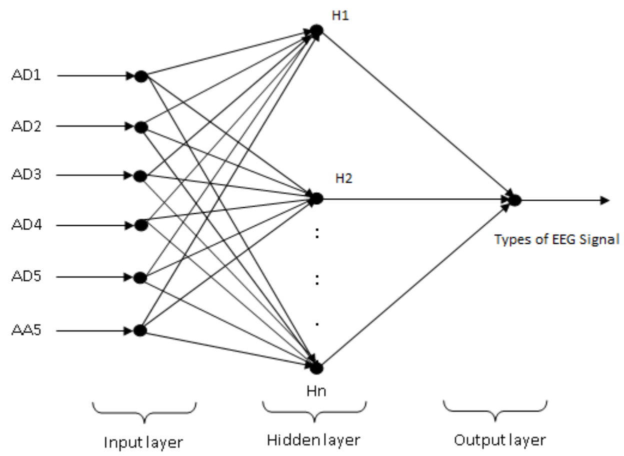
International Journal of Advanced Research in Computer and Communication Engineering
Vol. 5, Issue 3, March 2016

Feed Forward Neural Network (FFNN) is an artificial intelligence technique that is used to generate training data set for the applied input data. In this paper, a feed-forward neural network is used for identifying the types of EEG signal. A feed-forward neural network is a biologically inspired classification algorithm. It consists of a (possibly large) number of simple neuron-like processing units, organized in layers. Every unit in a layer is connected with all the units in the previous layer. These connections are not all equal; each connection may have a different strength or weight. The weights on these connections encode the knowledge of a network. Often the units in a neural network are also called node

The input layers of FFNN are AD1, AD2 , AD3, AD4 , AD5 and AA5 . The n numbers of hidden layers of neural network are H1, H2 ,..............Hn and the neural network process takes place in this hidden layer. The training of the neural network is performed by back propagation algorithm.

The output of neural network is used to determine the types of EEG signal. Using the neural network output, epilepsy affected brain signal is detected. the neural network, the multi-wavelet output is trained and the training dataset is generated for epilepsy detection. The weight between input and hidden layer is denoted as W1 , the weight between hidden and output layer is denoted asW2 .

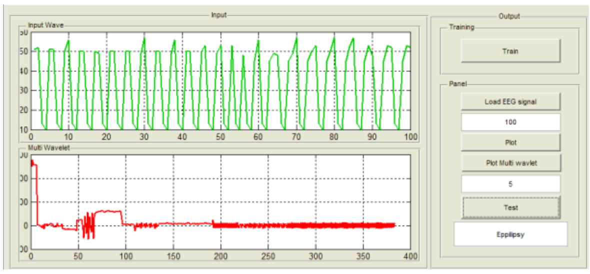
The weight adjustment depends on the output requirement. The formula for weight adjustment between the layers isWji (n □ 1) □ Wji (n) □ □Wji (n) .completed, then, the network is trained well for classifying the EEG signal. After the training process, the next process of neural network is testing. In this testing phase, an input signal is applied and then the types of EEG signal are calculated. From these types of EEG signal, the epilepsy can be detected.



Proposed Neural Network Training Structure

The above bar chart reveals that sensitivity, specificity, accuracy and precision of IApE are higher than conventional ApE.

Fig.8 shows the GUI of the proposed system.



GUI of proposed method system

In linear SVM 1, different theta values are taken but support vectors are fixed i.e. 400 and the results of classifications and misclassifications are shown. In linear SVM 2, by using training and test data sets, the results of classifications and misclassifications are shown where theta values and support vectors are fixed. In the experiment of AdaBoost SVM, AdaBoost tries to generate a strong classifier. It is done by using a linear combination of a set of weak classifiers which tries to find the best threshold to separate the data into two classes. In each classification step, the boosting part changes the weights of miss-classified data. So that, “weak classifiers” behaves as a “strong classifiers”.

Electroencephalography (EEG) signals give important information about neurobiological disorders and for feature extraction, DWT method is used. Different wavelet coefficients like maximum, minimum, mean and standard deviation are used. Then the result of classifications and misclassifications of Support Vector Machines (Linear and AdaBoost) for EEG signals are shown. AdaBooost SVM is used to convert a weak signal to a strong signal. EEG signal processing is a vast area of research. Different types of feature extraction techniques can be tried to reduce the computational complexity. Other new methodologies can be implemented in this area and further different types of classifiers like hybridize pattern classifiers, kernel SVM can be tested.

Support vector machine (SVM) is based on the principle of structural risk minimization. SVM learns an optimal separating hyper plane from a given set of positive and negative examples. This is in contrast to traditional pattern recognition techniques (Mourad Adnane et al., 2012; Marcus Musselman et al., 2010) of minimizing the empirical risk, which optimizes the performance on the training data. SVM can be used for pattern classification. For linearly separable data SVM finds a separating hyper plane which separates the data with the largest margin. For linearly inseparable data, it maps the data in the input space into a high dimension space.

To determine the maximum bandwidth for our signal (the ECG), one would over-sample a signal of the fastest heartbeat expected and then convert the signal into the frequency domain from the time domain. Looking at the signal in the frequency domain, the engineer will notice that the original waveform is made up of many (infinitely many) fundamental frequencies. By looking at the waveform in this fashion, the engineer can make a decision on how many of these frequencies she or he would like to include.This would be the maximum bandwidth of the signal.

EEG measures the electrical activity of the brain and represents a summation of post-synaptic potentials from a large number of neurons. EEG has several advantages over the other methods: its temporal resolution is higher and it directly measures the electrical activity of the brain. EEG has been a very useful clinical tool, especially in the field of epileptology, but also in other areas of neurology and psychiatry. Despite the fact that EEG is an important clinical tool for diagnosing, monitoring and managing neurological disorders, distinct difficulties associated with EEG analysis and interpretation, which hindered its wide-spread acceptance. Traditional method of analysis of the EEG is based on visually analyzing the EEG activity using strip charts. This is laborious and time consuming task which requires skilled interpreters, who by the nature of the task are prone to subjective judgment and error. Furthermore, manual analysis of the temporal EEG trace often fails to detect and uncover subtle features within the EEG which may contain significant information, Hence many researchers are working to develop an automated tool which easily analysis the EEG signal and revel important information present in the signal. Many research contribution already exist in the literatures that make use of epilepsy detection in EEG signal using different methods like template matching, Fourier Transfer, NN based approaches.This paper proposes a hybrid technique to classification of EEG signal for identification epilepsy seizure by combining MWT and ANN; also existing approximate entropy method (ApE) which is uses fixed window length for calculating irregularity present in the EEG signal is less accurate, to overcome fixed window length problem in ApE, the paper implemented an Improved Approximate Entropy (IApE).

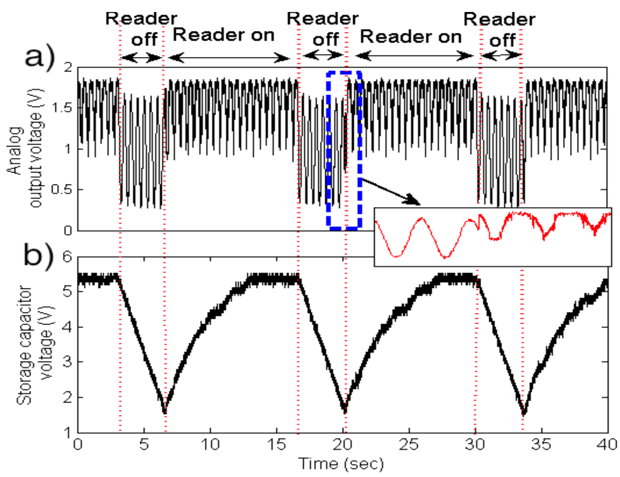
Numerous research works already exist in the literatures that make use of epilepsy detection in EEG signal. Important papers are reviewed below, for detailed review refer [20]. A wavelet-chaos-neural network methodology for classification of electroencephalograms (EEGs) into healthy, ictal, and interictal EEGs has been offered by Samanwoy Ghosh-Dastidar. In order to decompose the EEG into delta, theta, alpha, beta, and gamma sub-bands the wavelet analysis is utilized. Three parameters are used for EEG representation: standard deviation (quantifying the signal variance), correlation dimension, and largest Lyapunov exponent (quantifying the non-linear chaotic dynamics of the signal). The classification accuracies of the following techniques are compared: 1) unsupervised - means clustering; 2) linear and quadratic discriminant analysis; 3) radial basis function neural network; 4) Levenberg–Marquardt back propagation neural network (LMBPNN). The research was carried out in two phases with the intention of minimizing the computing time and output analysis, band-specific analysis and mixed-band analysis. In the second phase, over 500 different combinations of mixed-band feature spaces comprising of promising parameters from phase one of the research were examined. It is decided that all the three key components the wavelet-chaos-neural network methodology are significant for enhancing the EEG classification accuracy. Judicious combinations of parameters and classifiers are required to perfectly discriminate between the three types of EEGs. The outcome of the methodology clearly let know that a specific mixed-band feature space comprising of nine parameters and LMBPNN result in the highest classification accuracy, a high value of 96.7%. Gabor and Seyal [6] introduce a neural network algorithm that relies primarily on the spike field distribution. MLP networks with the number of input and hidden nodes equal to the number of channels in the record and a single output node are used. Five bipolar 8 channel records from the EMU with durations ranging from 7.1 to 23.3 min are used for training and testing. Two networks are trained on only the slopes of the spike's half-waves, and there is no notion of background context. The first uses the slope of the half-wave before the spike's apex for all 8 channels as inputs, and the second uses the slope after the apex. The output of the algorithm is a weighted combination of the two network outputs with a value near 1.0 indicating a spike has been found. The duration (not specified) of the spike half waves is fixed so that no waveform decomposition is required. The algorithm slides along the data one sample at a time and identifies a spike when the output is greater than a threshold (e.g. 0.9). The method requires a distinct network for each patient and spike foci, so 7 networks were trained because two of the patients had independent foci. The training required 4–6 example spikes and the non spikes were generated by statistical variation resulting in 4 times more non-spikes. Although this method does not seem to be well suited for general detection, it might be a promising method for finding 'similar' events. For the detection of seizure and epilepsy Hojjat Adeli et al. have offered a wavelet chaos methodology for analysis of EEGs and delta, theta, alpha, beta, and gamma sub-bands of EEGs. In the form of the correlation dimension (CD, representing system complexity) and the largest Lyapunov exponent (LLE, representing system chaoticity) the nonlinear dynamics of the original EEGs are quantified. The new wavelet-based methodology isolated the changes in CD and LLE in specific sub-bands of the EEG. The methodology was applied to three diverse groups of EEG signals i.e. healthy subjects, epileptic subjects during a seizure-free interval (interictal EEG), and epileptic subjects during a seizure (ictal EEG).The effectiveness of CD and LLE in distinguishing between the three groups is examined based on statistical importance of the variations. It has been noted that in the values of the parameters acquired from the original EEG there may not be noteworthy differences, differences may be recognized when the parameters were employed in conjunction with particular EEG sub-bands and concluded that for the higher frequency beta and gamma sub-bands, the CD distinguished between the three groups, in disagreement to that the lower frequency alpha sub-band, the LLE distinguished between the three groups. Subasi deals with a novel method of analysis of EEG signals using discrete wavelet transform, and classification using ANN. In this work the signal decomposed in 5 levels using DB4 wavelet filter .The energy of details and approximation were used as the input features. M.Akin, M.A.Arserim, M.K.Kiymik, I.Turkoglu have tried to find a new solution

IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 5, Issue 3, March 2016

for diagnosing the epilepsy. For this aim, the Wavelet Transform of the EEG signals have taken, and the δ, θ, α, and β sub frequencies are extracted. Depending on these sub frequencies an artificial neural network has been developed and trained. The accuracy of the neural network outputs is too high (97% for epileptic case, 98% for healthy case, and 93% for pathologic case that have been tested). This means that this neural network IJPHS 2252-8806 EEG Signal Classification for Epilepsy Seizure Detection using Improved …. (Sharanreddy) 25 identifies the health conditions of the patients approximately as 90 of 100. From this point we can say that an application of this theoretical study will be helpful for the neurologists when they diagnose the epilepsy. Xiaoli Li proposed an approach based on multi –resolution analysis to automatically indicate the epileptic seizures or other abnormal events in EEG. The energy of EEG signals at the different frequency bands is calculated for detecting the behaviors of brain during epileptic seizures. The energy change of each frequency band is indicated as a feature by calculating the Euclidean distance between a reference segment and the segments extracted in real time. The selection of wavelet functions, scale parameters, width of wavelet function, and sample sizes (segment length) are emphasized. Then, the features go through a recursive in-place growing FIR-median hybrid (RIPG-FMH) filter. The results suggest that wavelet transform is a useful tool to analyze the EEG signals with the epileptic seizures. Ganesan.M, Sumesh.E.P, Vidhyalavanya.R proposed a technique for the automatic detection of the spikes in long term 18 channel human electroencephalograms (EEG) with less number of data set. The scheme for detecting epileptic and non-epileptic spikes in EEG is based on a multi resolution, multi-level analysis and Artificial Neural Network (ANN) approach. The signal on each EEG channel is decomposed into six sub bands using a non-decimated WT. Each sub band is analyzed by using a non-linear energy operator, in order to detect spikes. A parameter extraction stage extracts the parameters of the detected spikes that can be given as the input to ANN classifier. The system is evaluated on testing data from 81 patients, totaling more than 800 hours of recordings.90.0% of the epileptic events were correctly detected and the detection rate of non-epileptic events was 98.0%



Oscilloscope reading, illustrating duty cycling of the reader: a) The output of the EEG acquistion circuit with a test sine wave. Enlarged plot shows corruption of the test signal, due to RF interference from the reader b) The EEGWISP's storage capacitor voltage changes as the reader is duty cycled

EEG Filters, Gain, References and DRL

We used the Texas Instruments MCP6044 for all operational amplifiers (op-amps) because the MCP6044 has quiescent current of 0.6A, one of the lowest on the market. The amplifier has a suitable gain–bandwidth product of 14 kHz, which allows gains up to 470 V/V (53.4 dB) at 30 Hz bandwidth.

1) A passive RC high-pass filter with cut-off frequency of 0.16 Hz eliminates the DC offset associated with the electrodes, which could otherwise saturate the circuit.

2) A gain stage allows fine tuning of the gain with a trimmer from 1 to 470 V/V (0 to 53.3 dB), which allows matching the amplitude of the amplified EEG signal to the analog-to-digital converter (ADC) range.

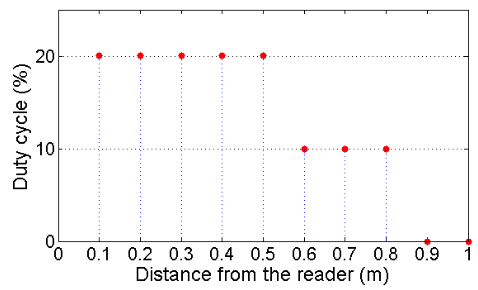
3) An antialiasing filter is a first order active filter with a fixed gain of 10 V/V (20dB). We chose a cut-off frequency of 30 Hz to satisfy the Nyquist Theorem, because it is half of the analog-to-digital converter's sampling frequency. We used an adjustable trimmer connected to the non-inverting op-amp input to eliminate the offset voltage.

4) We used a driven right leg circuit (DRL) as an active ground for the electrodes. The DRL has its name because historically it was attached to the right leg in electrocardiography (ECG). In this system, as is typically done with the EEG, the DRL is attached to the earlobe. The DRL actively rejects power line noise by implementing a feedback loop that samples the common-mode voltage and injects the current into the ground electrode.

5) We generated a reference voltage (Vdd/2) with a 1 M voltage divider (the high resistance reduces leakage current). To avoid loading, the voltage dividers were followed by an op-amp buffer.

Multi-Wavelet Transform Decomposition

In this MWT decomposition, the input signal is denoted as x(n) . The decomposed low pass filter outputs are denoted as A1, A2 , A3, A4 and A5 , and the decomposed high pass filter outputs are denoted as D1, D2 , D3, D4 and D5 . The Fig.2 shows the decomposition structure of MWT. Using this structure, the decomposition stage of EEG signal is calculated.



ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

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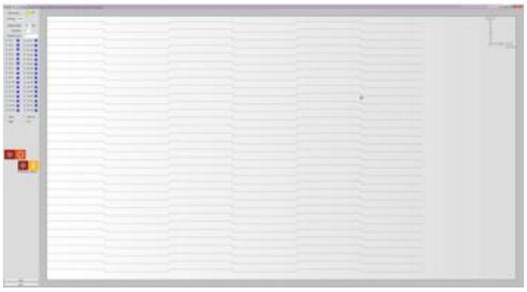
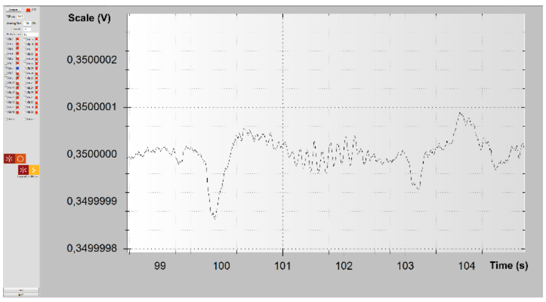
EEG signal streaming on PC is accomplished through a.NET

Framework application that was developed in C# programming language The open source Zed Graph library was also used for signal plotting. This library allows the configuration of virtually all plot parameters and is based on a User control structure. The developed application provides a TCP-IP socket server that establishes a connection to the client on a selected port. Once the connection is established and the data transmitted, the application begins to plot the signals in a graphical window. The developed application also provides online digital filtering and Fast Fourier Transform application. It provides the configuration of the number of channels to be displayed and the ability to save data into a file. Two classes were created in order to implement digital filters and Fourier Transform. Based on the 2nd order Butter worth topology, digital filters can be configured in band-pass, low-pass and high-pass mode. In which regards Fourier Transform, a class was created in order to display the power spectrum of the transformed signals. A set of EEG signals was acquired according to 2 different well-known conditions: alpha wave replacement and clenching jaw artifact. In Fig. 4, a square wave test signal is applied on the 32 acquisition channels.



PC Software developed for display of data streaming.

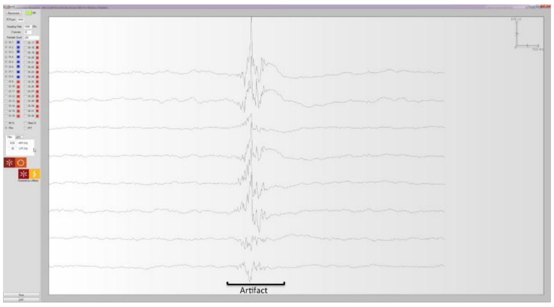
EEG recordings were evaluated through a alfa-wave replacement phenomenon [20]. The alpha rhythm appears on occipital regions of the scalp when the eyes are closed, and disappears when the eyes are opened [20].



Alfa rhythm during the eyes-closed and eyes-open conditions.

In this experiment, two bipolar dry electrodes were selected on the scalp of the subject, on the Cz and O1 positions, forming an EEG channel As it can be seen on Fig. 5, the platform acquired the two ocular events (opening and closing the eyes), and the alpha wave between them. Besides alpha rhythm and ocular artifacts, facial muscular artifacts (e.g. chewing movement) are often present as EEG sources of interference.

In a clenching jaw artifact was detected. In order to measure the input noise of the system, the ADS1299 differential inputs were short-circuited and a noise amplitude of about 3.1 µVpp was measured.



Clenching jaw artifact

Electroencephalogram (EEG) Ambulatory monitoring has been regarded as a promising tool to improve diagnosis, classification and medication prescription in patients with epilepsy and other paroxysmal diseases. This study presents the development of a wireless and wearable EEG acquisition system for ambulatory monitoring. The platform comprises 32 active dry electrodes, an analog-to-digital conversion unit with 24 bit resolution, 1 ksps sampling frequency per channel and a module for acquisition, processing and wireless transmission.

Healthcare consumes a large part of the gross domestic product of developed countries, and the trend is going upward . Solutions are thus needed to mitigate this issue. One possibility is to enable patients to participate in their own treatment by giving them the technological tools necessary to monitor and communicate their situation to caregivers. With recent advances in signal processing and very-low power wireless communications, wireless body sensor networks (WBSNs) have gained popularity as a potential solution. The use of various sensors located on the patient's body allows WBSNs to measure and communicate different physiological signals (e.g., heart and brain activity).

With respect to electrical brain activity, the electroencephalogram (EEG) signals are recorded using a collection of non-invasive wireless sensors located on a patient's scalp. These signals can then be used to detect different medical conditions, such as epileptic seizures. The detection of seizures through the use of a WBSN offers significant advantages. Because it is a relatively rare occurrence, seizure detection requires constant monitoring for an extended period of time, which is resource-intensive when carried in a health institution. Using an EEG WBSN can circumvent this by providing the patient a way to do the monitoring themselves and then consulting with a physician once the relevant data has been gathered.

Another important application of EEG signals in WBSNs is the use of a brain computer interface (BCI) that can detect the EEG patterns associated with a certain task performed by a patient. The patient could use a mental task (such as attempting to move a finger or some arithmetic task) to operate a wheel chair, switch a light off or communicate with the caregiver. As the signals associated with the mental task will be embedded in the

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ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
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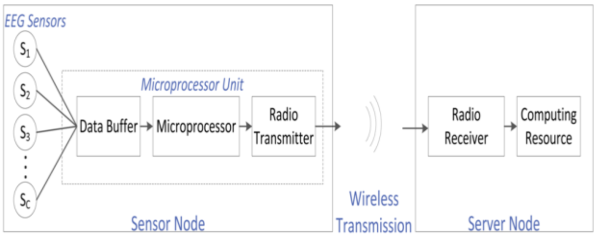
patient's EEG, the EEG signals are analyzed to detect their presence and, thus, operate a device. One of the main components required in the successful use of BCIs in a WBSN context is the development of advanced compression techniques that preserve the relevant information (or features) in the EEG signals.

Other common uses of EEG signals include sleep pattern studies and the diagnosis and treatment of strokes, infections (e.g., encephalitis, cerebral abscess), cerebral tumors and diseases (e.g., Alzheimer's) . In most of these cases, it is important to have a system that does not hamper the movements of the patient, hence why the cordless nature of WBSNs is valuable.

For an EEG-based WBSN, the EEG sensors are electrodes placed on a person's head, usually following an international convention (e.g., the international 10–20 system). An EEG sensor is also referred to as the EEG channel. The number of sensors depends on the application: some systems require few electrodes, while others require a few hundred. Every sensor is wired to a single central microprocessor unit that usually has three main components: a buffer (to store the EEG data stream coming from the different EEG channels; this buffer acts as memory), the microprocessor itself (to carry out computations needed before transmission) and a low-power radio (to wirelessly transmit the data). The combination of the EEG sensors and the microprocessor unit is referred to as the sensor node. This sensor node is battery powered. The sensor node transmits the EEG data to the server node wirelessly. The server node is comprised of two main blocks: a low-power radio receiver (to receive the transmitted EEG data) and a computing resource (to carry out any post-transmission computations, storage and any other desired operations). We assume that there is no constraint on the energy supply or the computational power at this server node



General block diagram for the electroencephalography (EEG) wireless body sensor network (WBSN) system.

The energy available in the battery powered sensor node in WBSNs is limited. This energy is needed for: (1) acquiring and digitizing the EEG samples; (2) carrying out the computations at the sensor node; and (3) wirelessly transmitting the data. Under current sensors technology, there is little that can be done to minimize the energy used for acquiring the signals; that is, the raw data must all be acquired and digitized. For computations carried out at the sensor node, energy savings could be realized by using algorithms that have low computational complexity. To minimize the amount of data transmitted, the acquired signals should be compressed before their transmission. A higher compression ratio will minimize the energy required for transmission. In other words, it is crucial to develop compression algorithms that do not require much computational energy.

Traditionally, measurements are collected by the sensors at the Nyquist rate. Then, lossy compression algorithms are directly applied to the raw data, prior to wirelessly transmitting them to the server node. This approach is undesirable for WBSNs, because of its high computational demand (and, thus, high energy consumption).

Recent research has demonstrated the advantages of using compressed sensing (CS) as an alternative compression scheme for physiological signals in the context of WBSNs. CS is a novel paradigm that allows the sampling of the signals at a sub-Nyquist rate. After acquiring the raw data, CS obtains a much smaller number of samples by taking linear projections of the raw data. This is a simple operation, which can be done at a low energy cost. The reconstruction of the data is, however, computationally complex and is allocated to the server node. As no constraints are placed on the computational power and energy resources of the server node, this makes CS appropriate in the context of WBSNs.

The first study that applied CS to EEG compression used the multiple measurements vectors (MMV) approach to compress and reconstruct the signals of the different EEG channels (i.e., all channels are reconstructed simultaneously). The obtained results were good (high compression ratio for reasonable reconstruction error), but this approach needed EEG signals from repeated trials (asking the patient to repeat the same task many times and recording one EEG channel each time). This setup increases the coherence in the signals (asking someone to carry out the same task is bound to result in EEG signals that are highly coherent). This setting is of limited interest in telemedicine applications, since in these applications, the patient is usually not prompted to act in a certain way or to repeat the same task multiple times.

For telemedicine applications, the first study that addressed the use of CS in EEG signal compression is found. This work focused on surveying existing sparsifying dictionaries and reconstruction algorithms and testing different combinations of these elements to determine which one yielded the best results. The conclusion was that the applicability of single-channel CS for EEG signals depended on the intended application and the tolerable reconstruction error.

More recently, Independent Component Analysis (ICA) was applied as a preprocessing step before using CS for compressing the EEG signals of newborn babies. The compression results obtained were superior to other state-of-the-art methods that do not employ ICA preprocessing. This system, however, consumes much energy at the sensor node and would not be suitable for telemedicine applications. This is because the ICA algorithm is computationally intensive, and such an operation must be carried at the sensor node. The results were later improved, but the computational complexity incurred at the sensor node remained too high for practical systems.

In, the focus was on developing an efficient hardware architecture for compressed sensing in the context of WBSN. This work demonstrates the potential gains of CS

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

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in such a context. However, it has some limitations. The hardware was developed so that it implemented a simple, single-channel version of CS. Limited testing was carried out when it comes to the reconstruction accuracy of the EEG application. Because it is a purely hardware-based architecture, any change in the architecture requires a hardware redesign. Furthermore, it is not possible to compare it against other frameworks unless someone builds the hardware, which is inconvenient.

The above studies resulted in some important questions: (i) What energy savings can be realized by using CS for EEG WBSN applications? (ii) Is it possible to exploit both the temporal correlations (intra-correlations) and the spatial correlations (inter-correlations between channels) to increase the compression performance of CS? (iii) How does CS compare with other state-of-the-art compression algorithms for EEG compression in WBSNs?

In this paper, we propose a novel CS framework that takes advantage of the inherent structure present in EEG signals (both temporal and spatial correlations) to improve the compression performance. To the best of our knowledge, this is also the first time that CS frameworks are compared with other state-of-the-art compression frameworks for EEG compression in WBSNs. It is also the first study where different types of EEG signals representing a variety of applications are used to test the performance of the proposed and existing frameworks, thus providing a more robust answer to the usefulness and validity of the systems.

The paper is organized as follows. Section 2 gives an overview of the theory underlying CS. Section 3 describes our algorithm and briefly introduces the benchmarking algorithms. Section 4 describes the experimental setup used for our experiments. Section 5 presents our results. Finally, Section 6 concludes the paper with suggestions for improvement and future work

Compressed Sensing

This section briefly discusses the key theoretical concepts behind compressing sensing: signal sparsity, signal acquisition and reconstruction, measurement incoherence and the extension to compressible signals.

Preprocessing

The data is first divided into non-overlapping line segments of length N. In our experiments, Ncorresponded to 512 samples for each channel. Note that our framework operates on data from one epoch at a time. Assuming we have C channels (sensors) of EEG data, after epoching, a total of Csequences of N = 512 data points each are obtained: f1, f2,…, fC. This forms a matrix, F. Each column of F contains one of the channels: FN×C = [f1|f2| … |fC].

The mean of each channel is then removed. The resulting matrix is F̃ = [f̃1|f̃2| … |f̃C]. The means will be added back in the reconstruction phase. Removing the means leads to a higher compression ratio, because the interchannel redundancy removal module (discussed later) performs better on demeaned EEG signals. It also reduces the total range of the signals, which makes it easier to quantize and encode them.

Compression

To compress the DE-mean ed EEG signals contained in one epoch, we first take their linear random projections and then apply an inter channel redundancy removal module.

Epilepsy is a common chronic neurological disorder. Epilepsy seizures are the result of the transient and unexpected electrical disturbance of the brain. About 50 million people world wide have epilepsy, and nearly two out of every three new cases are discovered in developing countries. Epilepsy is more likely to occur in young children or people over the age of 65 years; however, it can occur at any time. In epilepsy, the normal pattern of neuronal activity becomes disturbed, causing strange sensations, emotions, and behavior, or sometimes convulsions, muscle spasms, and loss of consciousness. There are many possible causes of epilepsy. Anything that disturbs the normal pattern of neuron activity ranging from illness to brain damage to abnormal brain development can lead to seizures. Epileptic seizures are manifestations of epilepsy. In the last couple of years, the EEG analysis was mostly focused on epilepsy seizure detection diagnosis. The methodology is based on three different adroit integration of computing technologies and problem solving paradigms (e.g., neural networks, wavelets, and chaos theory). Starting with template matching algorithm (find events that match previously selected spikes), which uses a statistical approach to compare the EEG signal with a data base of known epileptic spikes. This method lacks in the accuracy to detect the epilepsy.

Even though the optimized parameter set was defined on only three patients, the extremely low positive predictive value seen on Patient03 calls for either an improved robustness of the algorithm, by for instance designing a multi-parameter analysis, or a patient-specific solution for the parameter set. This latter suggestion has the drawback of requiring an expert to adjust the system according to the patient"s epileptic condition is likely to greatly improve the quality of the detection. It could also enhance the acceptation of the device by the surrounding family members and nursing staff since high sensitivity could be traded off with high positive predictive value. One possible way of improving the detection is to add additional modalities to the current system, such as 3D acceleration sensors. The fusion of motion and heart rate data is not currently supported by the ESD algorithm but it might help to filter out overnight activities [Thiemjarus, 2010] which also affect the heart rate such as rotating or going to the bathroom (see Figure 14). A multi-node approach could also be envisioned. It would gather not only physiological information from the heart but also acceleration from different body limbs. However, it might turn out to be too invasive for a part of the patient population.

The ECG monitor measures ECG at a sampling frequency of 200Hz. A real-time seizure detection algorithm is implemented in the ECG monitor. Alarms are wirelessly transmitted to the control unit synchronized with the video recording system. All data is stored pn-board for post-analysis. The resulting system is characterized in terms of:

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

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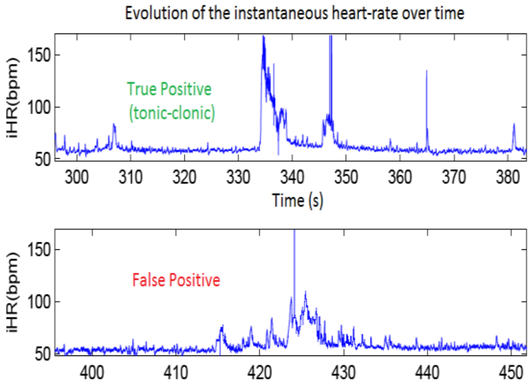
memory footprint, power consumption and algorithm execution time to ensure real-time deadlines are met. The embedded application requires 9.96KB of RAM, 26 KB of ROM. The maximum algorithm execution time is 176 ms. Average power consumption of the system is 8.9 mW. Moreover, a detailed analysis of the power consumption helps understanding the key challenges in extending the ECG monitor‟s autonomy.



The current ECG monitor implementation has more than one day of autonomy. Extending the battery life even further could benefit the field of epilepsy monitoring by, for instance, reducing the cost of care surrounding the daily setup of the system. As suggested by studying the pie chart in Figure 10, the ECG monitor‟s energy expenditure greatly depends on the functional requirements. For instance, removing the accelerometer from the sensor list would already save about 2.2 mW: 1 mW from the sensor, 0.8 mW from the SD-card writing and 0.4 mW from the ADC sampling representing 30% of the power budget dedicated respectively to the SD-card and to the ADC. Additionally, accessing the raw data is often not necessary and large storage component such as the SD card would not be required any longer which save again one fourth of the power budget (2.0 mW). Instead, low-power flash memory or the upcoming FRAM could be envisioned to only store processed information such as the heart rhythm or the output of the ESD algorithm. Finally, increasing the ECG monitor response time to a user‟s request, e.g. reducing the radio reception duty cycle of the LPL module, would give us back a few hundreds of microwatts.
To request the ECG monitor‟s battery level or a real-time snapshot of the ECG signal before starting a data collection, commands can be sent to the ECG monitor and will be processed as soon as the ECG monitor acknowledges the reception. For power-efficiency purposes, the uplink is achieved by using protocol derived from low-power listening (LPL) [Polastre, 2004] techniques. On one hand, the control unit sends periodically at a high frequency (200Hz/every 5 ms) a radio message to the ECG monitor. On the other hand, the ECG monitor is in receiving mode at much lower frequency to allow for power savings: 10 ms out of two seconds, yielding to a duty cycle ratio of 0.5% and a latency of two seconds. When a packet is received by the ECG monitor, it is then compared with the previous one to check whether an action is still needed.

Downlink : from the ECG monitor to the control unit
Regarding the downlink, from the ECG monitor to the base station, reliability and low-data rate are keys in designing the adequate radio protocol. Data traffic mostly consists in sporadic packet transmissions. This sporadic traffic generates no more than 400 samples per second, corresponding to a 2-second ECG snapshot that needs to be transferred within one second, and only few events per seconds corresponding to the selected output of the embedded algorithms. In the current implementation, one event or 16 samples can be transmitted per packet.
To cope with the required reliability of the radio link, a low-complexity, yet reliable Quality-of-Service (QoS) layer is implemented, adapted from [Massé, 2010]. The QoS layer distinguishes two types of traffic having different network requirements. On the one hand, burst traffic such as the one generated by the ECG-snapshot request does not require being highly data-consistent as it is only dedicated for data displaying. On the other hand, the event transmission shall be as reliable as possible as it can well trigger a life-critical alarm into the control unit. Moreover, the QoS protocol needs to account for event-priority handling and data freshness, newer events shall be transferred first. A single-entry non-blocking ring buffer was chosen to support the required buffering. On the one hand, each time a relevant event from the algorithm is required to be transmitted, it is buffered into the ring buffer and the writing key is incremented accordingly.
On the other hand, the ECG monitor application, , triggers a “radio transmission request” periodically every 5 ms (corresponding to a maximum of 200 events or 3200 samples per seconds, far beyond the requirements) allowing the QoS to wirelessly transfer one event or sample packet if available. As described in Figure 6, the QoS loops up to twice through the ring buffer backwards in time (from the most recent to the oldest event) to look for an unacknowledged packet. First it looks for a high-priority packet and then for a low-priority one, if necessary. Should one packet be found, it would then be transmitted over the wireless link. Depending on whether or not it has been acknowledged, it would either be stamped as “Acknowledged” and will not be sent any more, or have its retransmission counter incremented. To ensure that the payload date is not corrupted, the control unit acknowledges the received packet only after it passes successfully an integrity check (2-byte CRC).
The first transmission of an event is therefore guaranteed to occur within 5ms. A limitation in the number of allowed retransmissions .
The ECG monitor weights less than 20 grams with a dimension of 52x36x15mm³. The plastic box is strapped to the biceps, ensuring the sensor device to remain in place throughout the experiment. To reduce the amount of motion artifacts due to wiggling cables, an external connector allows for adapting the length of the electrode cables to the patient‟ morphology. To request the ECG monitor‟s battery level or a real-time snapshot of the ECG signal before starting a data collection, commands can be sent to the ECG monitor and will be processed as soon as the ECG monitor acknowledges the reception.

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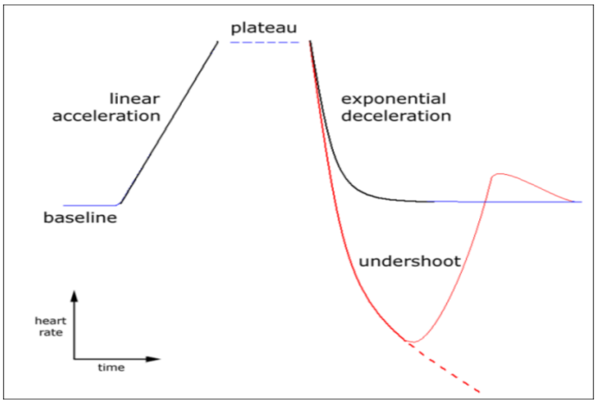
ISSN (Online) 2278-1021
ISSN (Print) 2319 5940
International Journal of Advanced Research in Computer and Communication Engineering
Vol. 5, Issue 3, March 2016



Heart rate patterns for seizure candidates.

For power-efficiency purposes, the uplink is achieved by using protocol derived from low-power listening (LPL) [Polastre, 2004] techniques. On one hand, the control unit sends periodically at a high frequency (200Hz/every 5 ms) a radio message to the ECG monitor. On the other hand, the ECG monitor is in receiving mode at much lower frequency to allow for power savings: 10 ms out of two seconds, yielding to a duty cycle ratio of 0.5% and a latency of two seconds. When a packet is received by the ECG monitor, it is then compared with the previous one to check whether an action is still needed or not.

VI.CONCLUSION AND FUTURE WORK

We implemented the project in curvelet based wavelet family to obtain coefficient models in overall wave distribution and analyze the seizure features in all classes like full sleep , semi sleep and unconscious stages through SVM classifier. The whole process will extend in More models like HMM , GMM models and classification in Neural Network to achieve better performance.

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