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Research paper



Acquiring and processing of female EEG signals of various wrist movements for neuro prosthetic applications

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Abstract

Human brain contain neurons which generate electrical signals, this can be recorded through electro encephalograph(EEG). Sensory motor cortices are responsible for motor activity i.e., various body movements, among which wrist movement reveals frequency change in Alpha & Beta bands of EEG signal. The aim of this approach is to calculate frequency changes responsible for various wrist movements such as flexion, extension, clockwise rotation and anticlockwise rotation, pronation and supination of female in both eyes open and eyes close conditions using FFT, wavelet transform classifier, where the largest set of EEG data is reduced to dimensions and the spectral frequencies for particular wrist movements are classified and the statistical analysis is done of various trials for both eyes open and eyes close conditions in both time domain and frequency domain and the mean and standard deviation of various trials will be compared for eyes open and eyes close condition in both time domain and frequency domain and these values can be implemented for neuro prosthetic applications.

Keywords: Electroencephalograph; flexion; Extension; fast fourier transform; classifier.

1. Introduction

A brain is the soft convoluted mass of tissue within the skull of vertebrates that function as the coordinating centre of sensation and nervous activity. The brain is the body's chief control centre, containing billions of interconnected nerve cells called neurons. Neurons communicate with each other through electrical signals with respect to internal/external motor/sensory stimuli. A large number of thousands or millions of neurons signals with synchronized activities can be detected on various scalp locations and are called brain signals (measured in cycles per second or Hertz). Electroencephalography (EEG) is an effective modality which helps to acquire brain signals corresponds to human behaviour in terms of motor and sensory states such as, eye movement, lip movement, remembrance, attention, hand clenching etc. from the scalp surface area. These signals are generally categorized as delta, theta, alpha, beta and gamma based on signal frequencies correspond to different types of brain activities which ranges from 0.1 Hz to more than 100 Hz, Satheesh Kumar, et.al., (2012). However, synchronized activity of a network of neurons shows oscillations at a variety of frequencies. Several of these oscillations have characteristic frequency ranges, spatial distributions associated with different states of brain functions. The neuronal networks underlying some of these oscillations are understood (e.g., the thalamocortical resonance underlying sleep spindles), while many others are not (e.g., the system that generates the posterior basic rhythm). Thereby, it is very difficult to get useful information from these signals directly in the time domain just by observing them. They

are basically non-linear and non-stationary in nature. Hence, important features can be extracted for the diagnosis of different diseases using advanced signal processing techniques, Subha D. P, et. al., (2010).

The electrical signal passes through the spinal cord and reaches the muscles that exert the necessary force. Current technology allows collecting and processing these electrical signals from the surface of the scalp area by placing surface electrodes on the scalp, vigneshwari, et.al., (2013). It consists of electrode paste which helps in better conductivity when using a surface electrode. Many systems typically use electrodes, each of which is attached to an individual wire. Some systems use caps or nets into which electrodes are embedded; this is particularly common when highdensity arrays of electrodes are needed. No matter whichever electrode has used the functions succeeding the signal acquisition is same. EEG represents the electrical activities of a brain by means of the graph. EEG have certain bands with separate frequency ranges theta waves varies in the range of 4 Hz to 7 Hz and its amplitude generally around 20 µV, alpha wave varies within the range of 8 to 13 Hz and about 30-50 µV amplitude. For a beta wave, the frequencies vary between 13 Hz to 30 Hz and usually have a low voltage between 5-30 µV. Different bands carry information about different brain activities, Aowlad Hussain A.B.M, et.al., (2015). After signal acquisition stage, signals are to be pre-processed because the acquired brain signals are most affected by noise and artifacts (unwanted signals). The artifacts that contaminated the EEG signals. To extract the feature matrix from the EEG signal, the artifacts have to be removed. The pre-



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processing step reconstructs the original brain activity by removing contained artifacts. To remove this we apply filtering process. The filters are optimal hence the maximum error between the desired frequency response and the actual frequency response is minimized. After pre-processing the features of EEG signals have to be extracted. Feature extraction is the process of extracting useful information from the signal, Lavanya T.H, et.al., (2010). A variety of different Feature extraction methods exist like Adaptive Auto Regressive parameters (AAR), Fast Fourier Transformations (FFT), PSE, Wavelet Transformations (WT), ICA, padmanabh Mahesh, et. Al., (2015). Extracted EEG signal further classified by using one of the techniques like LDA, QDA, SVM, KNN etc, Khan. Z. H, et. al., (2017).

2. Materials & Methods

2.1 Electroencephalography

The term "Electroencephalography" (EEG) is the process of measuring the brain's neural activity as electrical voltage fluctuations along the scalp that results from the current flows in brain's neurons, Mohammad, et.al., (2013). It is not only a function of time; it depends as well on the sensor position on the scalp of the experimental person. This is caused by the localization of the brain activity. Electroencephalography is an electrophysiological monitoring method to record electrical activity of the brain. Electrical recordings can be divided into invasive and noninvasive techniques. Noninvasive recordings are performed by measuring the electrical activity on the patients scalp by means of electrodes. The advantage of noninvasive technique is that it is cheaper, risk free and is easier, Gerrit, et. al., (2016). The system by which EEG electrodes are applied to the head then displayed on EEG recordings is called the International 10-20 system. The International 10-20 system is a standard of measuring the head and placing the electrodes. It depends on four main positions on the head that are easily transferable between the patients. First is the nasion at the bridge of the nose, next is the Inion at the boney prominent at the back of the head and then two Pre-auricular points just anterior to the ear. Each electrode is represented by a number and letter refer fig. 1 The numbers indicate the side of the head so that odd numbers are on the left and even numbers are on the right. In general, lower numbers mean that the electrodes are closer to the mid line, the midline itself is represented by z (zero). The letters are indicators of the position on head. F stands for frontal, C for central, P for parietal, T for temporal, O for occipital. The conventional scalp EEG is used to document the EEG signals. It consists of electrode paste which helps in higher conductivity whilst the use of a floor electrode. Many systems commonly use electrodes. That is connected to a person scalp.

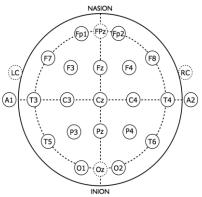


Fig.1: International montage system

2.2 Matlab

It is a high-performance language for technical computing. It integrates computation, visualization, and programming in an easy-to-use environment. It is an efficient tool which is used to extract the features and then these feature were processed in the excel application, Ramalingam. T, et. al., (2016). Toolboxes are comprehensive collections of MATLAB functions (M-files) that extend the MATLAB environment to solve classes of problems.

3. Proposed system

3.1. Signal acquisition

The electrodes are placed according to 10-20 International Montage system. Electrode paste helped the electrode to get secured to the scalp. The individual is asked to execute certain wrist movements and the EEG is recorded simultaneously. Movements include: Clockwise rotation, Anti-clockwise rotation, flexion and extension, Pronation and Supination. Each movement was attempted 20 times, with duration of 12s each, in both eyes open and eyes closed condition. The data was later sent and saved in a excel sheet. This procedure was carried for healthy male & female. This was done to ensure better comparison of EEG. The whole approach is shown in the figure. 2

3.2 Wavelet transform

Wavelet transforms are a mathematical means for performing signal analysis when signal frequency varies over time. For certain classes of signals and images, wavelet analysis provides more precise information about signal data than other signal analysis techniques. The basic function consists of wavelets, every one being a scaled and transformed version of identical wave. The wave transform makes it potential to study a characteristic in numerous scales at the same time. This is the most advantageous feature of wavelet transformation. Adding there to, the amount of resolution depends on the size, Lung Chuin Cheong, et. al., (2015).

3.3 Daubechies wavelet transform

The dbN wavelets are the Daubechies' extremal phase wavelets. N refers to the number of vanishing movements. The wavelets are characterized by a maximal number of vanishing movements for a given support. With each wavelet type of this class, there is a scaling function, which generates an orthogonal multi resolution. Each set of original data is fed as input say N; the wavelet function will be applied to calculate N/2. The steps included in iteration are calculation of scaling factor and wavelet function value. Every time the iteration continues by upgrading the value of i.

3.4 Wavelet decomposition and reconstruction

If we glance at what wavelet decomposition does, it breaks down a signal into a high and a lower part oppressing two filters and decimates by an element of two. It then repeats this on the approximation part (low) for every level you decompose. Thus, To decompose at one level, the signal could pass through each filter and decimate the result by two at the top. This preserves the number of total samples. an equivalent logic applies to following and ulterior levels. The whole procedure is inversed for wavelet reconstruction, Kumar. N, et al., (2017).

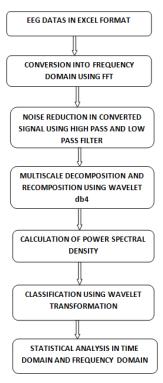


Fig. 2: Overall block diagram

3.5 Power Spectral Density

The power spectral density (PSD) is intended for continuous spectra. The integral of the PSD over a given frequency band computes the average power in the signal over that frequency band. The range of the frequency vector depends on the SpectrumType value. (PSD) is the frequency response of a random or periodic signal. It tells us where the average power is distributed as a function of frequency.

3.6 Statistical Analysis

Standard deviation it is the measure of how spread out the data is. A low SD denotes that the data points tend to be close to mean thus are not wide spread, while the high SD values indicates less closeness to mean and thus the data is wide spread.

Mean it is the foremost common and best general-purpose measure of the mid-point (around which all other values cluster) of a set of values, however is prone to distortion by the presence of extreme values and may need use of a measure of distortion (such as deviation or standard deviation). Additionally, known as arithmetic mean

Median it is the value separating the higher half of a data sample, a population, or a probability distribution, from the lower half. For a data set, it may be thought of as the "middle" value. The median is a commonly used measure of the properties of a data set in statistics and probability theory.

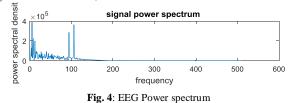
Mode of a set of data values is the value that appears most often. It is the value x at which its probability mass function takes its maximum value. In other words, it is the value that is most likely to be sampled.

4. Results And Discussion

EEG signals are obtained in Excel Format as shown in figure 3, and the Excel file for a particular movement is loaded as input in MATLAB program. Time period for each trial is about 10 seconds.

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	-95	73	15		420	-97	170					95 410				-55					
	-1177	859	16			-1124	1915					1075				-755					
	-1587	2144	-43			-1541	2645					1461				-1085					
	-1497	1047	-47		1190	-1510	2004					1404				-1133					
	-1020	675	-302			-1150						965				-928					
	-419	244	-91				-114					445				-633					
	85	-88	-60		76	-335	-1014					-20				-179					
	367	-252	-14			-112						-284				-230					
	336	-190	19	-407	-35	-137	-1337	1233	453	78	-490	-282	-1745	439	1278	-248					
	134	-25	35	-345	129	-293	-932	754	260	203	-540	-133	-1365	583	1007	-358					
		38	41	-152	198	-365	-691	493	1 138	123	-392	-36	-1206	370	875	-415					
	43	-54	43	-235	119	-302	-784	613	156	-65	-212	-83	-1300	405	967	-370					
	164	-200	57	-278	-17	-171	-984	883	264	-169	-156	-195	-1591	437	1139	-284					
	168	-237	75			-175						-223				-254					
	48	-158	71			-272						-164				-377					
	-19	-77	41			-328	-501					-125				-461					
	25	-57	24			-260						-243				-467					
	142	-89	7	-78		-177	-735					-213				-798					
	186	-87	7			-126						-222				-353					
	132	-38				-163	-631					-150				-369					
	78	-38	23			-185	-531					-66				-382					
4	60	- 102				-186	-501	- 443	172	- 4	-27	-13	-824	294	787	-371					_
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To have a better analysis of EEG signal, the signal is converted to frequency domain refer figure 4. The reason behind using FFT in this approach is, FFT is a simpler for EEG signals when the value of N is large. Basically, any time-dependent signal will be broken down in collection of sinusoids. In this way, prolonged and noisy EEG recordings will be conveniently plotted in a frequency power-spectrum. By doing so, hidden feature swill become apparent. By adding all the sinusoids up after FFT, the original signal will be restored, thus no data is lost.



EEG signals are extremely weak and affected by different types of noises and impairments that need to be carefully eliminated. Even though EEG signals are filtered during acquisition using notch filter; notch is a very selective filter with a very high rejection just for a tiny frequency band around the selected frequency. It will not attenuate other frequencies which belong to the EEG signal. So band pass filter is used additionally in the program refer figure 5. But it is very difficult to design a single band pass filter that can selectively eliminate the noises affecting the EEG. The filtering is accomplished by using multiple filters with specific purposes. So, both High pass filter and Low pass filter is used. The filtering is accomplished by using multiple filters with specific purposes.

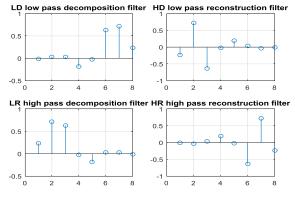


Fig. 5: Filtered EEG signal

The purpose of using multilevel wavelet decomposition in this approach is because multilevel wavelet decomposition provides the knowledge regarding frequency elements present and enhances the information about the signal for further processing. Wavelet decomposition breaks down the EEG signal into a high and a low part in pattern of to filters thus decimates by a component of two, which is shown in the figure 6. It then repeats this on the approximation part (low) for each level of decomposition. Therefore if the signal is decomposed at one level, then the signal is just passed through every filter and decimates the result by two at the highest. This preserves the quantity of total samples. An equivalent logic applies to following and ulterior levels.

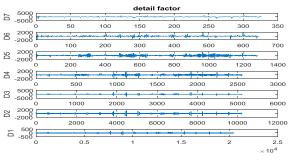


Fig. 6: Wavelet Decomposition

During reconstruction, detail coefficients and approximation coefficients at every stage are up sampled by two, passed by high and low pass synthesis filters and addedlater. To get the original signal, the method is continued by similar number of steps like decomposition method. The purpose of using Daub4 wavelet scaling is to illustrate how different types of signals are optimized for different scaling factors figure 7 (2, 4, 8, 16, 32, and 64).

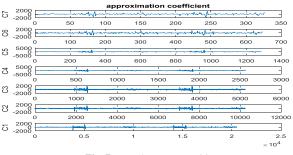


Fig. 7: Wavelet Recomposition

Power Spectral Density is calculated to find where the frequency variation is very high, and the frequency variation is very low. It reflects the 'frequency content' of the signal or the distribution of signal power over frequency. Peak value in the output image figure 8 denotes the corresponding frequency for the particular wrist movement.

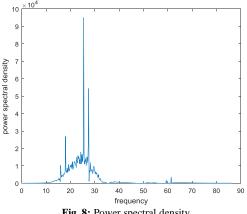
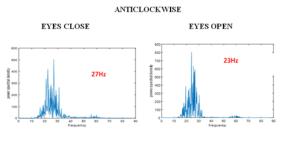


Fig. 8: Power spectral density

Comparison of eyes close and eyes open condition of all the wrist movements alongwith its statistical analysis such as frequency domain and time domain are shown in below.



ANTICLOCKWISE EYES CLOSE

TIME DOMAIN ANALYSIS

TIME DOMAIN ANALYSIS

FRE DOMAIN ANALYSIS

Min	0	0.0023126]	
Max	86.64	2147.78	1	
Mean	43.32	27.746	1	
Median	43.32	2.6048	Average	-0.50059
Mode	0	0.0023126	Standard	0.00000
Standard	25.08	172.158	deviation	64.35295
Deviation			kurtosis	
Range	86.64	2147.78		31.27593

ANTICLOCKWISE EYES OPEN

Min	0	0.0118145	7	
Max	86.64	13857.08		
Mean	43.32	26.976		
Median	43.32	3.8118	Average	0.4000
Mode	0	0.0118145	Standard	-0.49934
Standard Deviation	25.08	732.718	deviation	414.6078
Range	86.64	13857.08	KURIOSIS	9.85541

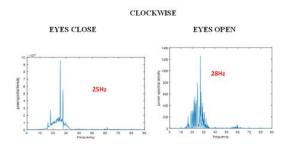
Fig. 9: Anticlockwise movement statistical analysis

The figure 9 shows the frequency data analysis and time data analysis for anti-clockwise rotation for female in eyes close and eyes open condition. Frequency data analysis is done for PSD after processing of signal takes place in frequency domain. Time data analysis is done for raw EEG signal without processing or filtration takes place in time domain. The mean value i.e. the frequency value for this particular movement is observed to be 27.746 in eyes close and 26.976 in eyes open condition. Whereas in time domain analysis the mean value is observed to be -0.50059 in eyes close and -0.49934 in eyes open condition. The average spread out of data i.e. SD of the Frequency analysis is 172.158 in eyes close and 732.718 in eyes open condition and for time domain is 64.352 in eyes close and 414.60 in eyes close condition.

The figure 10 shows the frequency data analysis and time data analysis for anti-clockwise rotation for female in eyes close and eyes open condition. Frequency data analysis is done for PSD after processing of signal takes place in frequency domain. Time data analysis is done for raw EEG signal without processing or filtration takes place in time domain. The mean value i.e. the frequency value for this particular movement is observed to be 21.516 in eyes close and 25.763 in eyes open condition. Whereas in time domain analysis the mean value is observed to be -0.50025 in eyes close and -0.49949 in eyes open condition. The average spread out of data i.e. SD of the Frequency analysis is 1427.798 in eyes close and 596.176 in eyes open condition and for time domain is 140.9393 in eyes close and 93.08799 in eyes close condition.

The figure 11 shows the frequency data analysis and time data analysis for anti-clockwise rotation for female in eyes close and eves open condition. Frequency data analysis is done for PSD after processing of signal takes place in frequency domain. Time data analysis is done for raw EEG signal without processing or filtration takes place in time domain.

FRE DOMAIN ANALYSIS



CLOCKWISE EYES CLOSE

TIME DOMAIN ANALYSIS

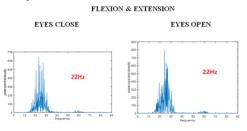
Min	0	1.729063]		
Max	86.64	21354.34	1		
Mean	43.32	21.516	-		
Median	43.32	62.4678	Average		
Mode	0	1.729063	-	-0.50025	
Standard Deviation	25.08	1427.798	 Standard deviation 	140.9393	
Range	86.64	21354.34	kurtosis	31.64301	

CLOCKWISE EYES OPEN

FRE DO	MAIN ANAI	ANSIS	TIME DOMAIN	ANALYSIS	
Min	0	0.0034151]		
Max	86.64	10768.5			
Mean	43.32	25.763			
Median	43.32	2.71314	Average		
Mode	0	0.0034151		-0.49949	
Standard	25.08	596.176	 Standard deviation 	93.08799	
			kurtosis	100020000	
Range	00.04	10768.5	1.154/365/C34/254/C34/	4.651081	

Fig. 10: clockwise movement statistical analysis

The mean value i.e. the frequency value for this particular movement is observed to be 29.712 in eyes close and 26.627 in eyes open condition. Whereas in time domain analysis the mean value is observed to be -0.49932 in eyes close and -0.4995 in eyes open condition. The average spread out of data i.e. SD of the Frequency analysis is 112.976 in eyes close and 112.976 in eyes open condition and for time domain is 371.94 in eyes close and 422.134 in eyes close condition



FLEXION & EXTENSION EYES CLOSE

FRE DOMAIN ANALYSIS

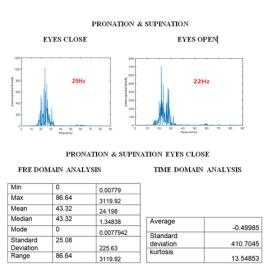
TIME	DOMAIN	ANALYSIS

Min	0	0.001813		
Max	86.64	1283.7		
Mean	43.32	29.712		
Median	43.32	0.99778	Average	-0.49932
Mode	0	0.001813	Standard	0.40002
Standard	25.08		deviation	371.9469
Deviation		112.976	kurtosis	
Range	86.64	1283.7		13.55089

FLEXION & EXTENSION EYES OPEN

FRE DOM	MAIN ANAL	YSIS	TIME DOMAIN A	ANALYSIS
Min	0	0.001813	7	
Max	86.64	1283.7	7	
Mean	43.32	26.627		
Median	43.32	0.99778	Average	
Mode	0	0.001813		-0.4995
Standard Deviation	25.08	112.976	Standard deviation	422.1347
Range	86.64	1283.7	kurtosis	35.77343

Fig. 11: Flexion & Extension movement statistical analysis



	PRONATION & SUPINATION EYES OPEN						
FRE DOM	MAIN ANAL	YSIS	TIME DOMAIN	ANALYSIS			
Min	0	0.0120302]				
Max	86.64	947.8	1				
Mean	43.32	25.402					
Median	43.32	1.12278	Average				
Mode	0	0.0120302	Standard	-0.50061			
Standard Deviation	25.08	92.328	deviation	572.5202			
Range	86.64	947.8	kurtosis	60.80827			

Fig. 12: Pronation & Supination movement statistical analysis

The figure 12 shows the frequency data analysis and time data analysis for anti-clockwise rotation for female in eyes close and eyes open condition. Frequency data analysis is done for PSD after processing of signal takes place in frequency domain. Time data analysis is done for raw EEG signal without processing or filtration takes place in time domain. The mean value i.e. the frequency value for this particular movement is observed to be 24.196 in eyes close and 25.402 in eyes open condition. Whereas in time domain analysis the mean value is observed to be -0.49985 in eyes close and -0.50061 in eyes open condition. The average spread out of data i.e. SD of the Frequency analysis is 225.63 in eyes close and 92.326 in eyes open condition and for time domain is 410.704 in eyes close and 572.52 in eyes close condition.

5. Conclusion

This approach proposed that EEG frequencies of female for various wrist movements such as flexion and extension, anticlockwise rotation and clockwise rotation, pronation and supination have been extracted in both eyes open and eyes close condition through 10 - 20 electrode system. The obtained frequencies are almost similar to that of the alpha and beta rhythms of brain signals, i.e the frequencies lies between 22 and 28 Hz. From the observed frequency range beta waves are more prominent during these movements. Since the variations of frequency for each movement is very small, it can be analyzed through the classification techniques. These processed frequencies can be used for neuro prosthetic applications.

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