Real Time Sleep Detection System Using New Statistical Features of the Single EEG Channel

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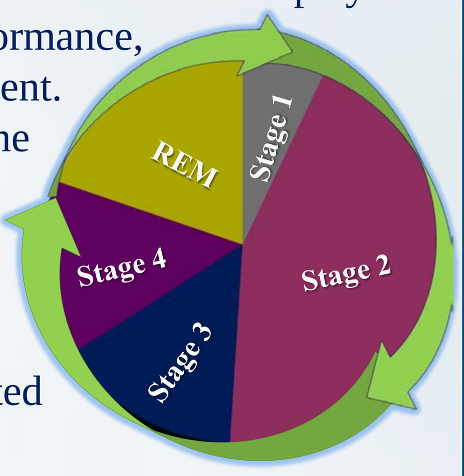
Abstract

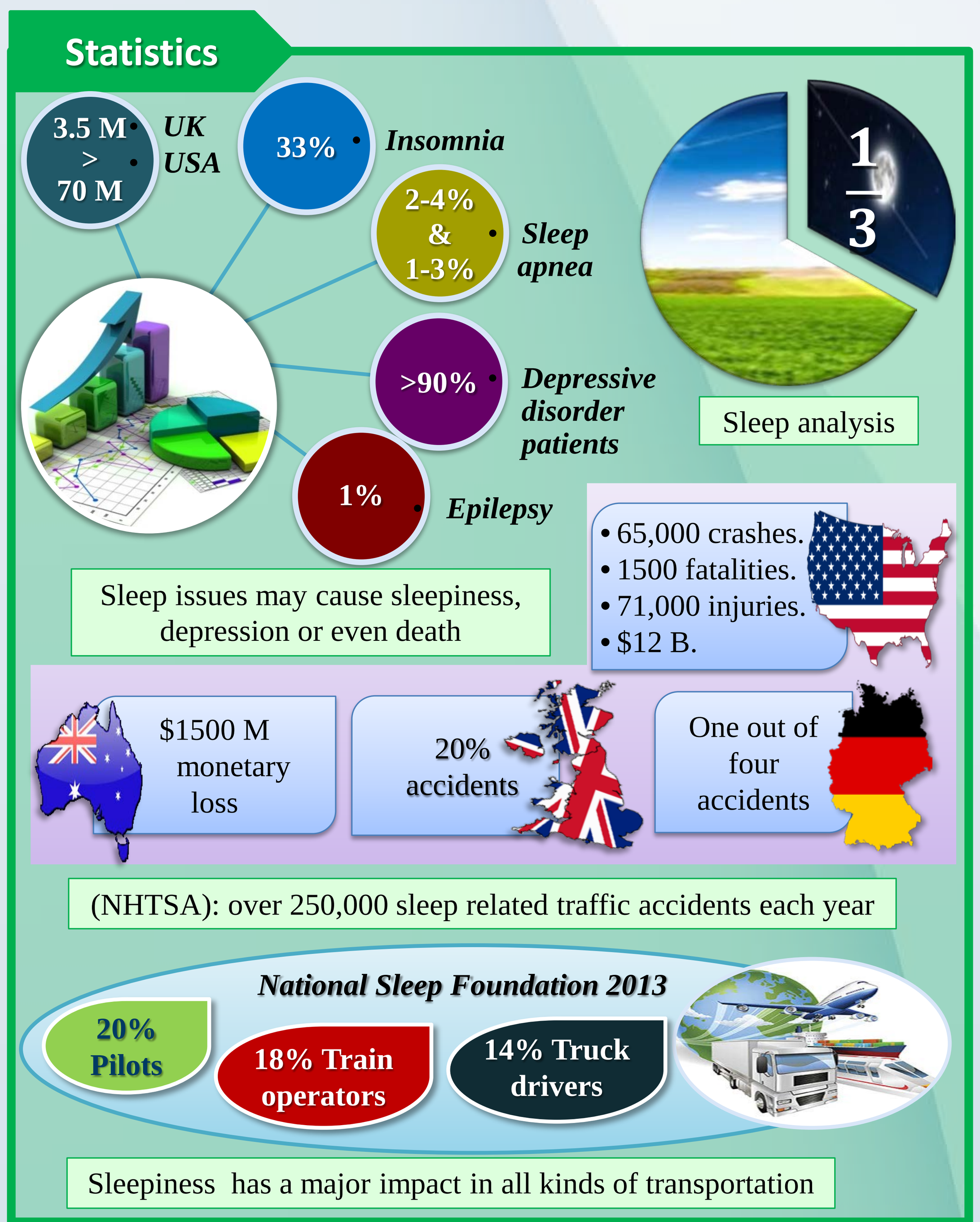
Sleep specialists often conduct manual sleep stage scoring by visually inspecting the patient's neurophysiological signals collected at sleep labs. This is, generally, a very difficult, tedious and time-consuming task. The limitations of manual sleep stage scoring have escalated the demand for developing Automatic Sleep Stage Classification (ASSC) systems. Sleep stage classification refers to identifying the various stages of sleep and is a critical step in an effort to assist physicians in the diagnosis and treatment of related sleep disorders. Many of the prior and current related studies use multiple EEG channels, and are based on 30s or 20s epoch lengths which affect the feasibility and speed of ASSC for real-time applications. Thus, the aim of this work is to present a novel and efficient real time technique that can be implemented in an embedded hardware device to identify sleep stages using new statistical features applied to 10 s epochs of single-channel EEG signals. First, we run our algorithm off line using the PhysioNet Sleep European Data Format (EDF) Database to classify six sleep stages. The proposed methodology achieves an average classification sensitivity, specificity and accuracy of 89.06%, 98.61% and 93.13%, respectively, when the decision tree classifier is applied. Second, our new method is compared with those in recently published studies, which reiterates the high classification accuracy performance. Finally, we propose an effective EEG classification technique for detecting sleep to only prove that our algorithm is simple and works fast in real time in an efficient way using Neurosky Mindwave headset that gathers the user's brain waves.

Significance

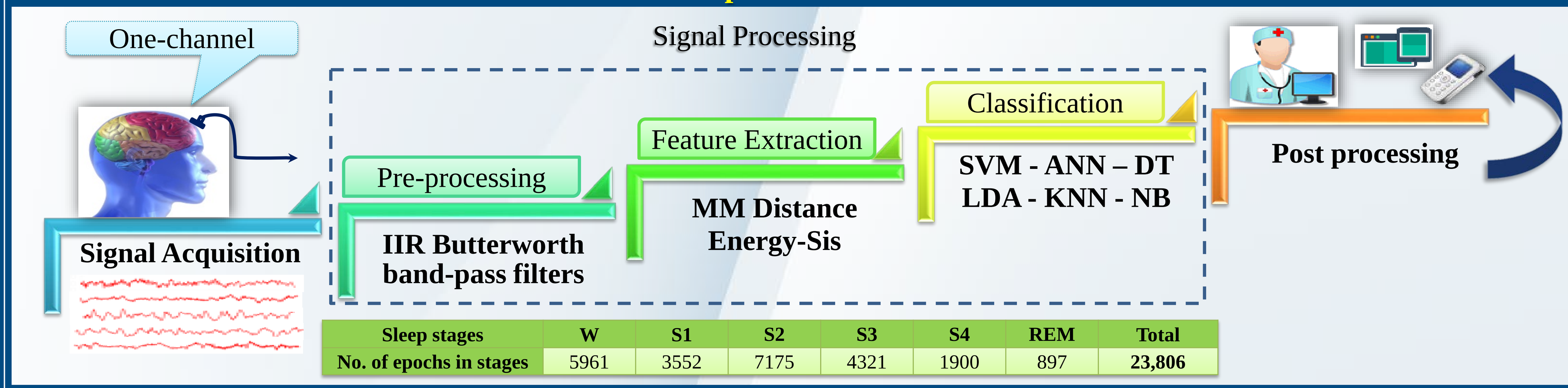
Sleep is the primary function of the brain and plays an essential role in an individual's performance, learning ability and physical movement. Sleep is a reversible state in which the eyes are closed and several nervous system centers are inactive. Hence, sleep renders the individual either partially or completely unconscious and makes the brain a less complicated network. Humans spend around one-third of their lives sleeping and conditions such as insomnia and Obstructive Sleep Apnea (OSA) are frequent and can severely affect physical health.



Statistics

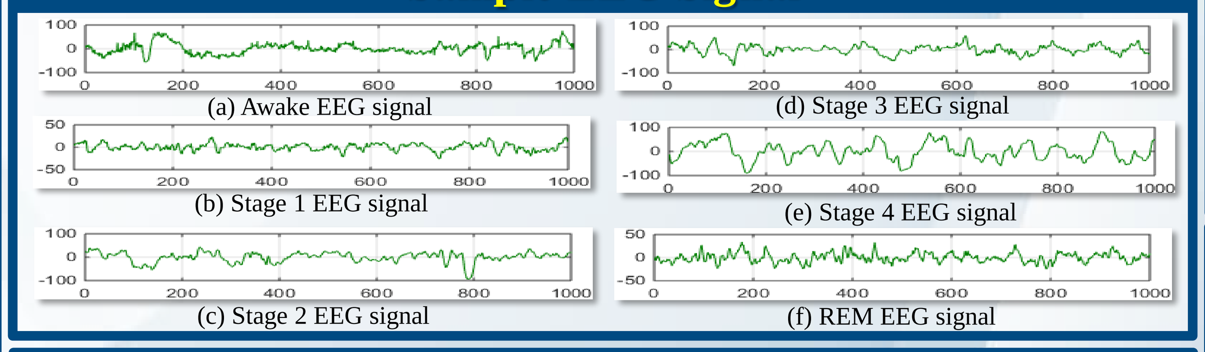


Proposed Method



Sleep stages	W	S1	S2	S3	S4	REM	Total
No. of epochs in stages	5961	3552	7175	4321	1900	897	23,806

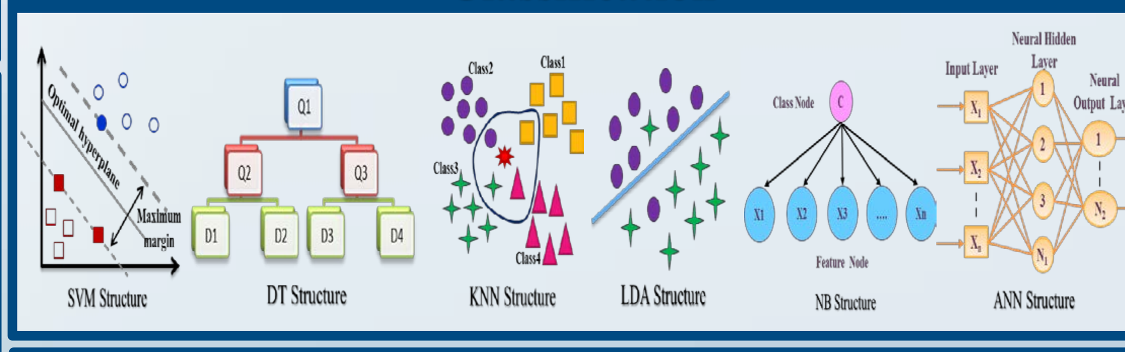
Sample EEG Signal



Data Decomposition

Rhythm	Delta Δ	Theta θ	Alpha α	Beta β	Gamma γ
Frequency	0-4 Hz	4-8Hz	8-12Hz	12-22Hz	>30Hz
Amplitude	20-100μV	10μV	2-100μV	5-10μV	-

Classification

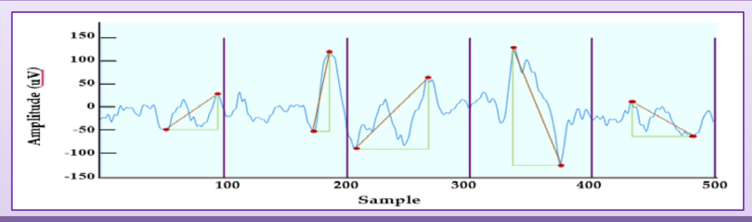


New Feature Extraction

Because EEG is considered a non-stationary signal, and unlike stationary signals, has no specific patterns, the signal was segmented in the time domain into sub-windows to apply the first feature, ***Maximum-Minimum (MM)-distance.*** The second feature, which determines the energy and speed of the EEG signal, is ***EnergySis***. The assumption is that the number of samples (or length) of a sub-window is considered to be a power of 10, that should start from 100. This number is also used as the wavelength of the EEG waveform. In a generalized form,

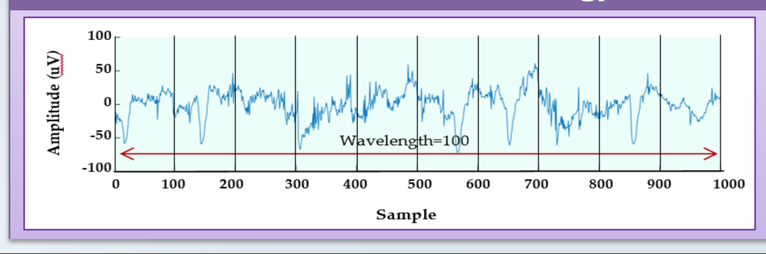
$$\lambda = \begin{cases} 100 & if \quad n < 10,000 \\ 10^{\lceil logn \rceil - 1} & if \quad n \geq 10,000 \end{cases}$$

MM Distance



$$MMD = \sum_{i=1}^{w} |d_i|$$

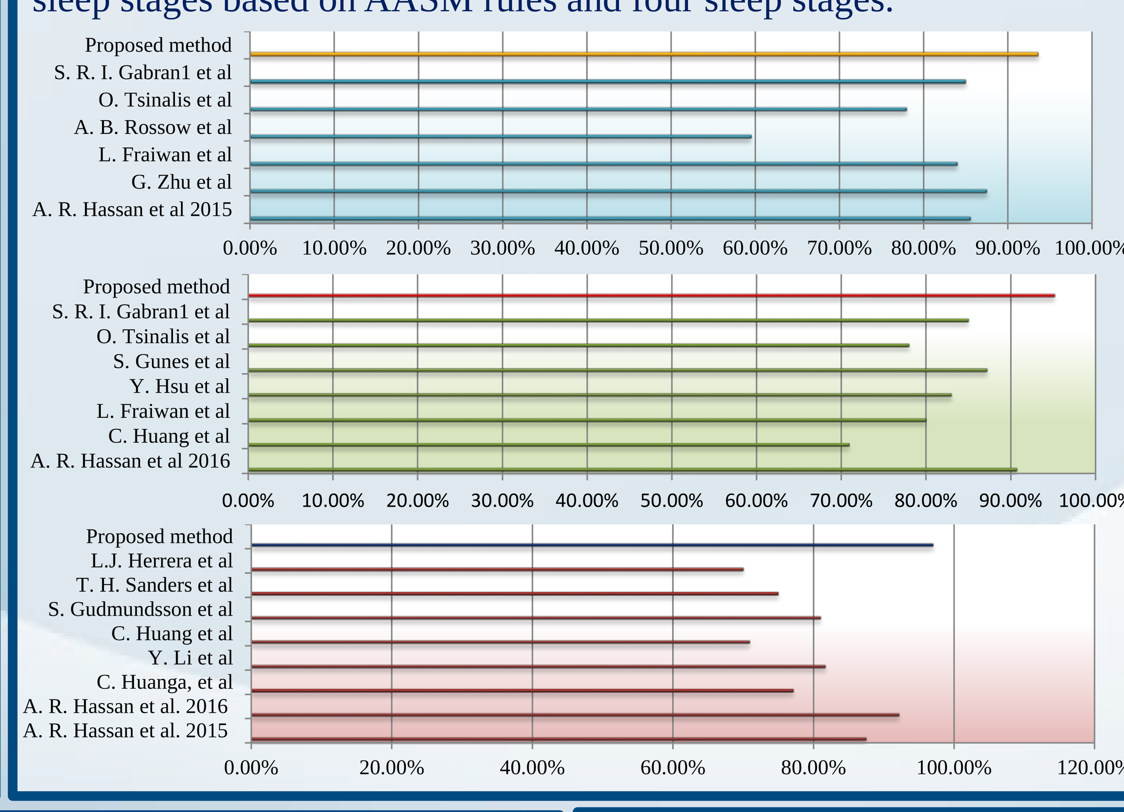
EnergySis



$$Esis = \sum_{i=1}^{N} |X_i^2| \times v$$

Comprehensive Comparison

The methods that classify the six sleep stages using R&K standard, five sleep stages based on AASM rules and four sleep stages.



Off Line System Results

Confusion matrix for 4-stage classification

Test percentage		S1+S2	S3+S4	Wake	REM	A_{cc}
20	S_e	96.33	98.19	98.13	70.05	96.30
	S_p	97.11	99.05	99.49	98.93	
30	S_e	95.50	98.52	98.24	68.63	95.98
	S_p	97.21	98.81	99.30	98.87	
50	S_e	96.41	98.00	97.82	64.85	95.90
	S_p	96.19	99.32	99.49	98.81	

Test percentage		S1+REM	S2	S3+S4	Wake	A_{cc}
20	S_e	96.22	95.76	98.14	97.92	96.99
	S_p	99.00	98.52	98.90	99.52	
30	S_e	95.53	96.36	98.32	98.69	97.29
	S_p	99.12	98.55	99.32	99.34	
50	S_e	94.48	96.64	97.76	98.15	96.89
	S_p	99.27	97.94	99.13	99.42	

Confusion matrix for 5-stage classification

Test Percentage		S1	S2	S3+S4	Wake	REM	A_{cc}
20	S_e	92.53	96.34	97.82	97.88	67.23	95.46
	S_p	98.71	98.33	99.00	99.58	98.71	
30	S_e	91.18	96.38	97.42	97.28	72.14	95.19
	S_p	98.87	98.04	98.96	99.47	98.62	
50	S_e	91.40	95.54	97.49	97.73	66.88	94.87
	S_p	98.40	98.10	99.01	99.44	98.64	

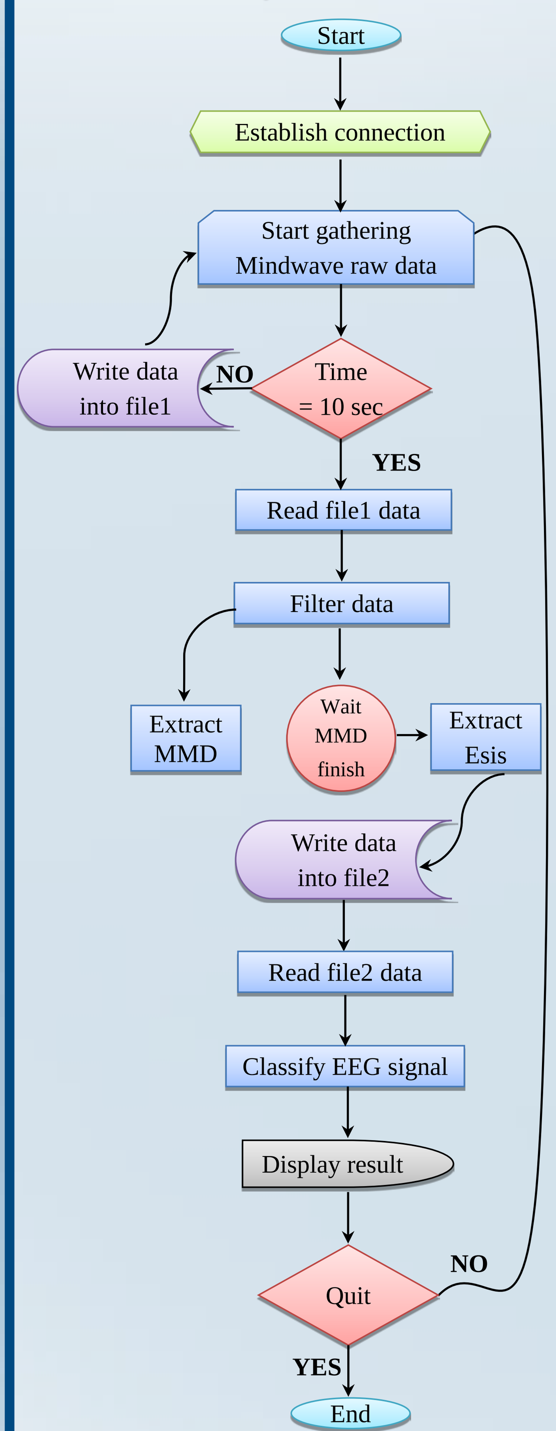
Confusion matrix for 6-stage classification

Test percentage		S1	S2	S3	S4	Wake	REM	A_{cc}
20	S_e	91.19	96.43	91.25	86.88	98.64	66.32	93.29
	S_p	98.59	98.09	98.10	98.70	99.44	98.94	
30	S_e	91.06	95.84	90.95	86.15	97.41	76.26	93.18
	S_p	98.89	97.91	98.13	98.87	99.55	98.40	
50	S_e	91.46	95.05	90.83	87.60	97.63	72.22	92.92
	S_p	98.58	98.16	98.11	98.72	99.32	98.58	

Neurosky Mindwave

An effective EEG sleep detection technique has been proposed to prove that our algorithm is simple and works fast in real time in an efficient way. The presented approach uses Neurosky Mindwave which is the obtainable, smallest and affordable EEG headset that gathers the user's brain waves.

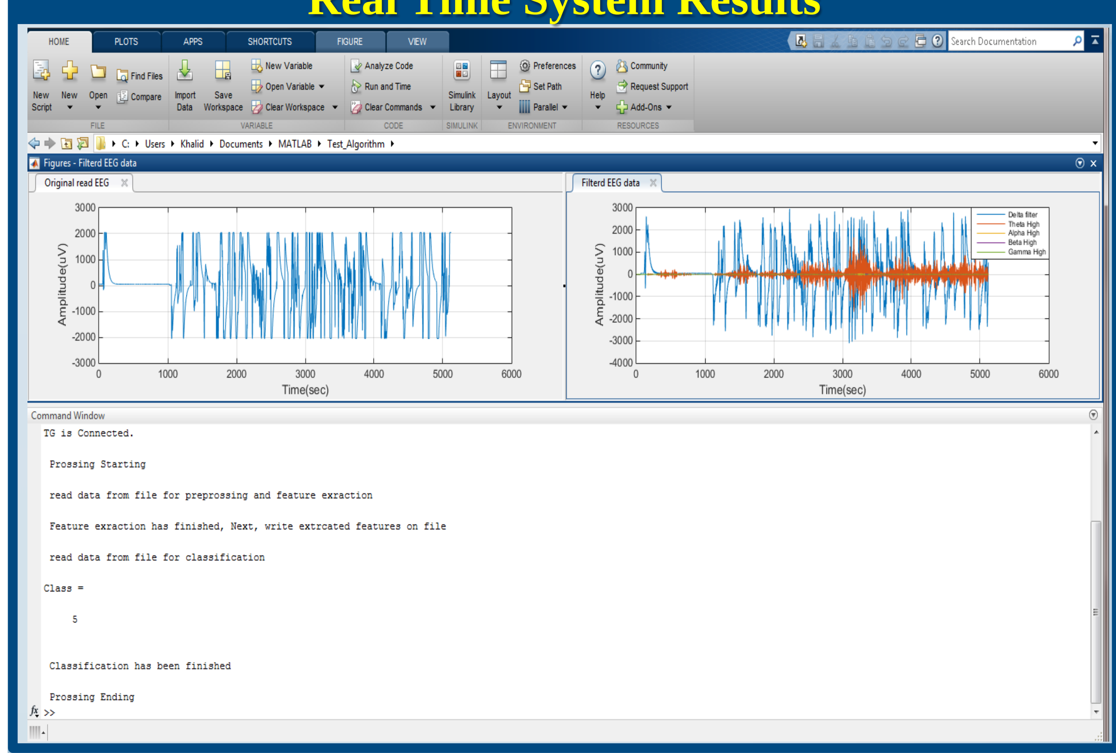
Real Time System Flowchart



Algorithm Time Complexity

Feature	No.	Statement	Running time	Time Complexity
MMD	1	strP=1;	T(n) =1	O(1)
	2	endP=range;	T(n) =1	O(1)
	3	for i=1:hSize	T(n) = 2n	O(n)
	4	sgmD=xd(strP:endP);	T(n) = 2+n	O(1)
	5	[Mi,Imi] = min(sgmD);	T(n) = n log n	O(n log n)
	6	[Mx,Imx] = max(sgmD);	T(n) = n log n	O(n log n)
	7	disD=disD+abs (sqrt((Mx-Mi).^2+(Imx-Imi).^2));	T(n)= 9n	O(n)
	8	strP=endP+1;	T(n)= 2n	O(n)
	9	endP=endP+range;	T(n)=2n	O(n)
Esis	10	sgmD=[];	T(n)=n	O(n)
	11	end	T(n)=1	O(n)
	12	Dfreq= Fstop/2;	T(n) = 2	O(1)
	13	vd= Dfreq*range;	T(n)=2	O(1)
	14	for i=1:el	T(n)=2m	O(m)
	15	Ed=Ed+((abs(xd(i))^2)*vd);	T(n) =6m	O(m)
	16	End	T(n) = 1	O(1)

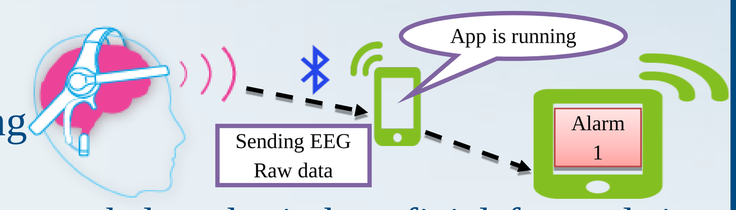
Real Time System Results



Execution Time

The performance measurement for our algorithm takes to run is 0.7844 sec while the response of our system from initial connection between Mindwave and MATLAB until the EEG classified is approximately 15.0697 sec which is the actual time. Essentially, if this time is segmented and analyzed, the 10 sec is for recoding the data and the 5.07 is for our algorithm. Thus, approximately yielding the actual execution time of our algorithm.

Future Work and Conclusion



The new, simple statistical features developed in this work, called EnergySis and Maximum-Minimum Distance, provided an effective approach for analyzing the 10s EEG signal capability for measuring and identifying brain activity states [1]. The use of 10 s epoch lengths is beneficial for real-time applications. Since the MindWave device and most smart phone devices integrate with Bluetooth, future work can be extended to build a capable App software that will work on smart phone operating systems (OS) such as IOS and Android devices. Therefore, our simpler, quicker and more feasible scheme makes our approach attractive for easy implementation in any embedded devices to identify certain patterns such as fatigue, drowsiness and/or various sleep disorders (e.g., sleep apnea) in real-time.

Reference: [1] Aboalayon, K.A.I.; Faezipour, M.; Almuhammadi, W.S.; Moslehpour, S. Sleep Stage Classification Using EEG Signal Analysis: A Comprehensive Survey and New Investigation. *Entropy* **2016**, *18*, 272.