An Investigation of How Wavelet Transform can Affect the Correlation Performance of Biomedical Signals

The Correlation of EEG and HRV Frequency Bands in the frontal lobe of the brain

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Abstract: Recently, the correlation between biomedical signals, such as electroencephalograms (EEG) and electrocardiograms (ECG) time series signals, has been analysed using the Pearson Correlation method. Although Wavelet Transformations (WT) have been performed on time series data including EEG and ECG signals, so far the correlation between WT signals has not been analysed. This research shows the correlation between the EEG and HRV, with and without WT signals. Our results suggest electrical activity in the frontal lobe of the brain is best correlated with the HRV. We assume this is because the frontal lobe is related to higher mental functions of the cerebral cortex and responsible for muscle movements of the body. Our results indicate a positive correlation between Delta, Alpha and Beta frequencies of EEG at both low frequency (LF) and high frequency (HF) of HRV. This finding is independent of both participants and brain hemisphere.

1 INTRODUCTION

Biomedical signals are a record of electrical activity within human body, and they may indicate the state of health of human. Among many biomedical signals, Electroencephalograph (EEG) and Electrocardiograph (ECG) signals are considered in this work. EEG signals provide a measure of brain nerve cell electro-physiological activity, that is accessible on the surface of the scalp (Lewis et al., 1988), thus provide information about different types of brain activity. Identifying changes in EEG signals has improved our understanding of the relationship of these signals to people ′s moods, and behaviour (Han et al., 2012), (Ebersole and Pedley, 2003). ECG signals contains a plethora of information on the normal and pathological physiology of the heart and its health. Furthermore, ECG signals provide vital information with regards to the function and rhythm of the heart. The heart rate variability (HRV) has been extracted from the ECG signals. HRV describes the variation in time between consecutive heart beats, which is commonly referred to as the RR (R wave to R wave) or NN (Normal beat to normal beat) intervals.

In recent years, the correlation between the EEG and the ECG have been conducted to analyse their functionality under certain conditions and to check whether this functionality is related to each other. Research (Kim et al., 2013), (Chua et al., 2012), (Abdullah et al., 2009), (Sakai et al., 2007), (Berg et al., 2005), (Edlinger and Guger, 2006), suggests that the correlation between spectral bands of EEG and HRV has been conducted to assess the interaction between them, and achieved remarkable correlation.

The recent research on correlation between these two signals as mentioned earlier has focused on the Fourier analysis of the frequencies presents in these signals. Whilst, the wavelet transform (WT), acts on frequency and time of the recorded signals. Therefore, WT has widely utilized for analysing biomedical or time series signals. The WT of the signal can be thought of as an extension of the classic Fourier transform (FT) - it works on multi-scale basis, instead of working on a single scale (Time or Frequency) as FT, and gives detailed and clear information of the signals. Therefore, WT of the signals is an important method not only to analyse EEG and ECG/HRV signals individually, but also to analyse the correlation between them. According to recent research (Thomas and Moni, 2016), (Chandra et al., 2017), (Mirsadeghi et al., 2016), (Mporas et al., 2015), (Valderrama et al., 2012), (Nasehi and Pourghassem, 2011), (Cvetkovic et al., 2008), WT has been used to analyse either EEG or ECG signal, but the correlation between these transformed signals has not yet been conducted. In this paper we are not only focusing on the correlation between without wavelet transform signals but also between wavelet transformed signals.

2 RELATED WORK

A series of data points in time order, or time series, provide the view of a signal as it evolves over time, in the Time domain (TD). TD analysis is used to analyse the signal in its actual state - it is utilised to analyse changes in biomedical signals, such as the power (or amplitude) over time. In addition, the frequencies present in the signal are open to investigation (for example, by using the Fast Fourier Transform (FFT)). Such an analysis is said to take place in the Frequency domain (FD). The FD analysis is used to identify frequencies present in the signals. Furthermore, it can be utilized to establish the relationship between frequencies and its corresponding power (amplitude), and so the energy distributions in signals.

In recent research, the correlation between EEG and ECG/HRV signals have been analysed in the FD ,as shown in Table 1, which indicates that the Pearson correlation is the best method for the FD analysis. In addition, different numbers of EEG electrodes have been used to analyse the relationship with the ECG/HRV. To the best of our knowledge, very limited work has been done on the correlation between EEG and ECG/HRV signals using 19 EEG electrodes. Moreover, no one has analysed these signals under the same condition (i.e. with TEAS acupuncture applied) that utilised in this research. This paper investigates the correlation between EEG and ECG/HRV signals in FD using Pearson correlation considering all 19 EEG electrodes under the same condition.

Based on the research as shown in Table 2 on WT, it is straightforward that the DWT based methods are well known for EEG and ECG feature extraction and analysis. Furthermore. Among the DWT based methods mentioned, *db wavelet* method has been considered by the researchers. It is obvious from the research on WT that key features of EEG and ECG signal can improve the analysis performance. Therefore, it is important to analyse not just either EEG or ECG as shown in Table 2, but also the correlation between EEG and ECG. To our knowledge, we have not yet found information on the correlation between wavelet transformed signals. In this work, we describes such an analysis.

3 DATASET INFORMATION

Two different datasets were obtained with each of them containing different numbers of participants, stimulation location, and total time length as shown in Table 3. All of these datasets follow the 10-20 electrode placement system shown in Figure 1. The 10-20 system is the recognized method to describe the location of electrodes (Klem et al., 1999). The values of 10 and 20 percentage shown in Figure 1 refer to the distances between adjacent electrodes: either 10 or 20 percentage of the total front-to-back or right-to-left distance over the skull - front-to-back distance is based on the measurement from the Nasion (point between forehead and nose) to the Inion (lowest point of the skull from the back of the head indicated by a prominent bump), and right-to-left distance is based on the measurement between the left and right preauricular ear points.
Dataset 1 and 2 consist of EEG and ECG recordings from 16 and 7 participants, respectively. These data were obtained over ten 5 minutes slots with eyes open using Transcutaneous Electro Acupuncture (TEAS) method, including resting state data in the first and the last slot. The EEG and ECG recording were made simultaneously. 19 electrodes (Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, and O2) for EEG recording were used, following the 10-20 system. The sampling rate used for EEG was 250Hz, and the reference was to linked ear electrodes. For ECG data, two electrodes were placed on both side of the wrist (having one electrode as ground) to record the electrical activity of the heart over time, and the sampling rate used was 256Hz.

Table 3: Information about the Datasets.

Label	Dataset 1	Dataset 2
Number of Participants	16	7
EEG-Electrodes	19	19
EEG-Sampling Rate	250Hz	250Hz
ECG-Electrode	1	1
Stimulation Location	1	4
ECG-Sampling Rate	256Hz	256Hz
Total Time Length	50 minutes	45 minutes
Slot Time Length	5 minute	5 minute

The difference between these datasets, other than the participants, is the body location where TEAS stimulation has been performed. For Dataset 1, only one body location (Dominant Hand), and for Dataset 2, four different body location (Left Hand, Below Left Knee, Right Hand, and Below Right Knee) has been used to perform TEAS stimulation.

Table 1: Summary of Correlation Research on Biomedical Signals since 2003 to 2017

RefDetail	TD	FD	Pearson Correlation Method	Other Correlation Method	EEG Electrodes Investigated
(Miyashita et al., 2003)	-	✓	✓	-	4
(Yang et al., 2002)	-	✓	✓	-	2
(Ako et al., 2003)	-	✓	✓	-	1
(Jurysta et al., 2003)	-	✓	-	Coherency Analysis	3
(Takahashi et al., 2005)	-	✓	✓	-	6
(Edlinger and Guger, 2006)	-	✓	✓	-	2
(Berg et al., 2005)	-	✓	✓	-	2
(Sakai et al., 2007)	-	✓	✓	-	19
(Abdullah et al., 2010)	-	✓	-	Cross-correlation	1
(Chua et al., 2012)	-	✓	-	✓	4
(Kim et al., 2013)	-	✓	-	Coherency Analysis	19
(Prinsloo et al., 2013)	✓	-	✓	-	3
(Liou et al., 2014)	-	✓	✓	-	19
(Triggiani et al., 2016)	-	✓	✓	-	19

Table 2: Summary of Research on Well known Wavelet Transformation Methods for Biomedical Signals since 2012 to 2017

RefDetail	EEG	ECG/HRV	TD	FD	Feature Extraction Method
(Kutlu and Kuntalp, 2012)	-	✓	✓	-	DWT-Daub Wavelet
(Thomas et al., 2015)	-	✓	✓	-	DWT-Daub Wavelet
(Sudarshan et al., 2017)	-	✓	✓	-	DWT-Daub Wavelet
(Acharya et al., 2017)	-	✓	-	✓	DWT-Daub Wavelet
(Dolatabadi et al., 2017)	-	✓	✓	✓	Principal Component Analysis (PCA)
(Kumari et al., 2014)	✓	-	✓	✓	DWT-Daub Wavelet
(Mumtaz et al., 2017)	✓	-	✓	✓	DWT-Daub Wavelet
(Kevric and Subasi, 2017)	✓	-	-	✓	DWT-Daub Wavelet
(Faust et al., 2015)	✓	-	✓	-	DWT-Daub Wavelet

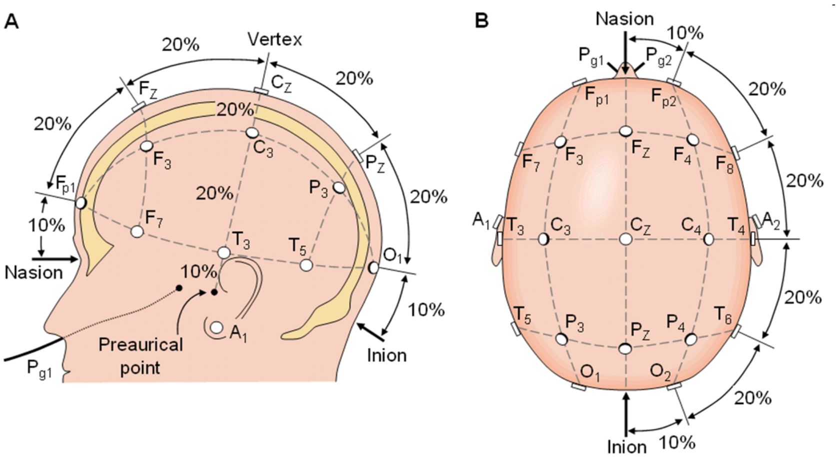

Figure 1: The international 10-20 system seen from A (left side of the head) and B (above the head). The letter F, T, C, P, O, A, Fp and Pg stands for frontal, temporal, central, parietal, occipital, earlobes, frontal polar, and nasopharyngeal, respectively. The figure is obtained from (Klem et al., 1999).

4 METHODS

4.1 Pearson Correlation

The Pearson′s correlation coefficient measures how closely two different observables are related to each other. Correlation co-efficient range between 1 (when the matching entities are exactly the same) and -1 (when the matching entities are inverses of each other). A value of zero indicates no relationship existing between the entities.

4.2 Wavelet Transform

The Wavelet Transform (WT) is designed to direct the problem of signals with nonstationarity. It includes representation of time function in terms of simple blocks, termed wavelets. These blocks are derived from a signal generating function called the *mother wavelet* by translation and dilation operations. Dilation, also known as scaling, compresses or stretches the mother wavelet and translation shifts it along the time axis (Daubechies, 1990), (Akay, 1997), (Unser and Aldroubi, 1996). The WT can be categorized into continuous and discrete. Continuous wavelet transform (CWT), implies that the scaling and translation parameters change continuously, and thus, represent considerable effort and vast amount of data calculation for every possible scale. Therefore, we used discrete wavelet transform (DWT). The WT of the signal can be thought of as an extension of the classic Fourier transform (FT) - it works on multi-scale basis, instead of working on a single scale (Time or Frequency) as FT. This is achieved by decomposition of the signal over dilated (scale) and translated (time) version of wavelet. An input signal is decomposed by using low pass filter and high pass filter followed by down sampling in each stage. The output of the first stage high pass filter gives the detail coefficient (D1), whereas the low pass filter gives the approximation coefficient (A1).

The prototype wavelet used in this study is Daubechies wavelet of order 4 (db4) based on our research on biomedical/time series signal analysis, as mentioned in Table 2.

5 EXPERIMENTAL SET-UP

The experimental steps are shown in Figure 2. The EEG signals were pre-processed to remove artefacts caused by the electrical activity in muscles including eye, jaw and muscle movements using Independent Component Analysis (ICA). It was straightforward to remove these using ICA (Hyvärinen and Oja, 2000). The power spectrum for each frequency band of EEG - Delta (0.3-4 Hz), Theta (4-7.5 Hz), Alpha (7.5-13 Hz), Beta (13-30 Hz), and Gamma (30-50 Hz) were then obtained by Power Spectrum Density (PSD) (Stoica and Moses, 1997).

To extract HRV from ECG signals, we used method designed by Lin et al. (Lin et al., 2010). The results of the automatic analysis were reviewed and any errors in R-wave detection and QRS labelling were then removed manually. R-R interval data obtained from the edited time sequence of R-wave and QRS labelling were then transferred to a personal computer. In order to remove artefact from extracted HRV signal, each R-R interval has been compared against a local average interval. If an R-R interval differs from the local average more than a specified threshold (Threshold in seconds) value, then that R-R interval is defined as an artefact and is replaced with an interpolated value using a cubic spline interpolation. The power spectrum for each frequency band of HRV - Very Low Frequency (VLF) ranges 0-0.04 Hz, Low Frequency (LF) ranges 0.04-0.15 Hz, and High Frequency 0.15-4 Hz were then obtained by PSD (Power Spectrum Density).

The sampling rate is 1Hz for the extracted HRV, and 250Hz for the EEG. In order to perform correlation between these different sampling rate signals, it was required to change the sampling rate for either the EEG or HRV signals. Therefore, we decided to segmenting EEG signals using 1 second window and represent each window by its means value (the mean value from each 250 samples), unlike normal down sampling, where much of the data is thrown away. For each participant's EEG data, this process has been repeated for all 5 minutes slots. After windowing, the spectral analysis was performed. From each frequency bands of the EEG and the HRV, the mean of the amplitude value within the frequency range has been measured, single value for each of these frequency band, and for each 5 minute is obtained. Then, the correlation between these frequency values is performed.

In order to perform correlation based on wavelet transformed EEG and/or HRV signal, the WT-*Daubechies (db) Wavelet* up to level 5 is performed on the signals before extracting frequency bands as mentioned in Figure 2. For the datasets we have, the low pass filter worked very well. Therefore, we considered low passed WT signals to perform the correlation.

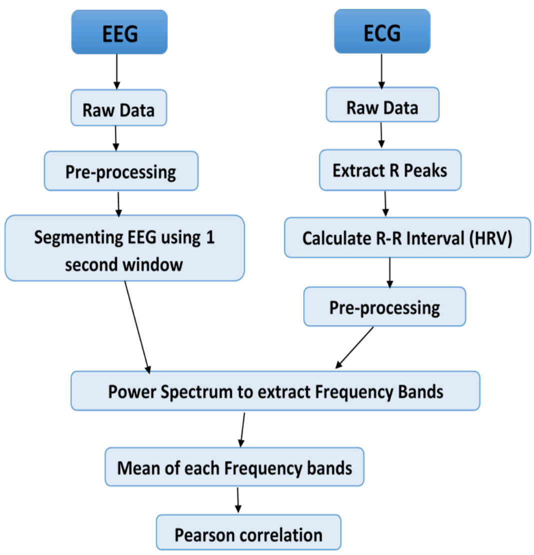

Figure 2: Experiment steps for the correlation performance.

6 EXPERIMENTAL RESULTS AND DISCUSSION

For each dataset, we investigated the correlation between each of the EEG frequencies (Delta, Theta, Alpha and Beta) with each frequencies of the HRV frequencies (LF and HF) in three different experiments: 1). The Correlation between Pre-processed Signals, 2). The Correlation between Pre-processed and WT signals of the EEG and HRV, and finally 3). The Correlation between Pre-processed HRV with Pre-processed and WT signals of the EEG. The Gamma frequency of EEG did not give us the correlation effect. Therefore, it is not considered in the result shown in Figure 3 and Table 4.

For both datasets, the experiment 2). correlation between both WT signals did not give better results, because HRV is tend to be less noisy. Therefore, when the WT has been performed on HRV, information has been lost and the signal became more flat. The most interesting result has been found from experiments 1). and 3).

For each frequency combination correlation, the average of participants for each EEG electrode has been calculated. Then the best performance electrode has been ranked- where, the ranking has been given based on electrode correlation result. The average of electrode ranking for each frequency combination is then gathered and five best performance electrodes result has been looked closely. We have found some common electrodes in all of the frequency combination we have investigated. Figure 3 shows the result of this investigation for Dataset 1 and 2.

As shown in Figure 3, for dataset 2, some electrodes from the back side of the brain are giving stronger result than dataset 1. This is due to more randomness in the EEG signals from dataset 2. Also, the location where TEAS has been performed might contributed to this result.

Based on results shown in Figure 3, it can be seen that the frontal lobe of the brain is correlated with the heart. The frontal lobe involved in higher mental functions, such as concentration, creativity, speaking, muscle movement and in making plans and judgements, is a part of cerebral cortex (body's ultimate control and information processing) of the brain (McCraty et al., 2009). The usual Heart-Brain communication path is through spinal cord. In order to have relationship between frontal lobe of the brain and heart, we assume the communication might have done through 'Medulla'(cardiovascular center placed in medullacontrols the heart beating) which is part of brain stem. The signal has been then directed to the Thalamus and then to the cerebral cortex (Lane et al., 2001), (ATKINSON and BRADLEY, 2004).

Table 4 shows the average correlation result of participants for each frequency comparison from dataset 1 and 2. Where, Level 0 means correlation between pre-processed data, and Level 1 to 5 means, correlation between pre-processed HRV with pre-processed and WT EEG. The heat map of these result ("Red" is strongest and "Dark-Blue" means weakest) as shown in Table 4, indicates the correlation performance changes with the levels of WT. We found the signal became flat after level 2, and lost information when levels has been increased. Therefore, we have not considered result of levels 3, 4 and 5 in Figure 3 (b) and (d).

Results shown in Table 4 are indicative and not statistically significant, according to these, three frequencies of EEG have shown some correlation, such as Delta, Alpha, and Beta, have shown correlation at both LF and HF of HRV. Each of these frequencies represent the activities of these signals. For example, Delta will be higher if the person is in deep sleep, Alpha will appear if the person is calmed, relaxed or in creative visualisation, and Beta will show if the person is working or feeling more alert. For HRV, LF and HF represent the sympathetic and parasympathetic activities of autonomic nervous system (ANS), respectively.

7 CONCLUSIONS

The main conclusion of this work is that electrical activity in the frontal lobe of the brain is correlated with the HRV for the given two datasets. To the best of our knowledge this is a new result. This suggests that most probably the electrical signals could be transmitted through the cerebral cortex, Thalamus, and Medulla of the brain (Saper et al., 2005). The possible path of the key neuronal projections that maintain alertness is shown in Figure 4.

The second conclusion from this work is that, WT signals also give correlation from the frontal lobe of the brain. To the best of our knowledge, the correlation between WT signals of EEG and ECG/HRV has not yet been investigated.

A more tentative conclusion of this work is that three frequencies of the EEG Delta, Alpha and Beta are correlated with the LF and HF of HRV, for dataset 1 and dataset 2, respectively. Whereas, most of previous studies, (Yang et al., 2002),(Ako et al., 2003),(Jurysta et al., 2003),(Abdullah et al., 2010) and (Chua et al., 2012), have shown negative correlation between these frequency bands due to the condition in which these signals have been analysed.

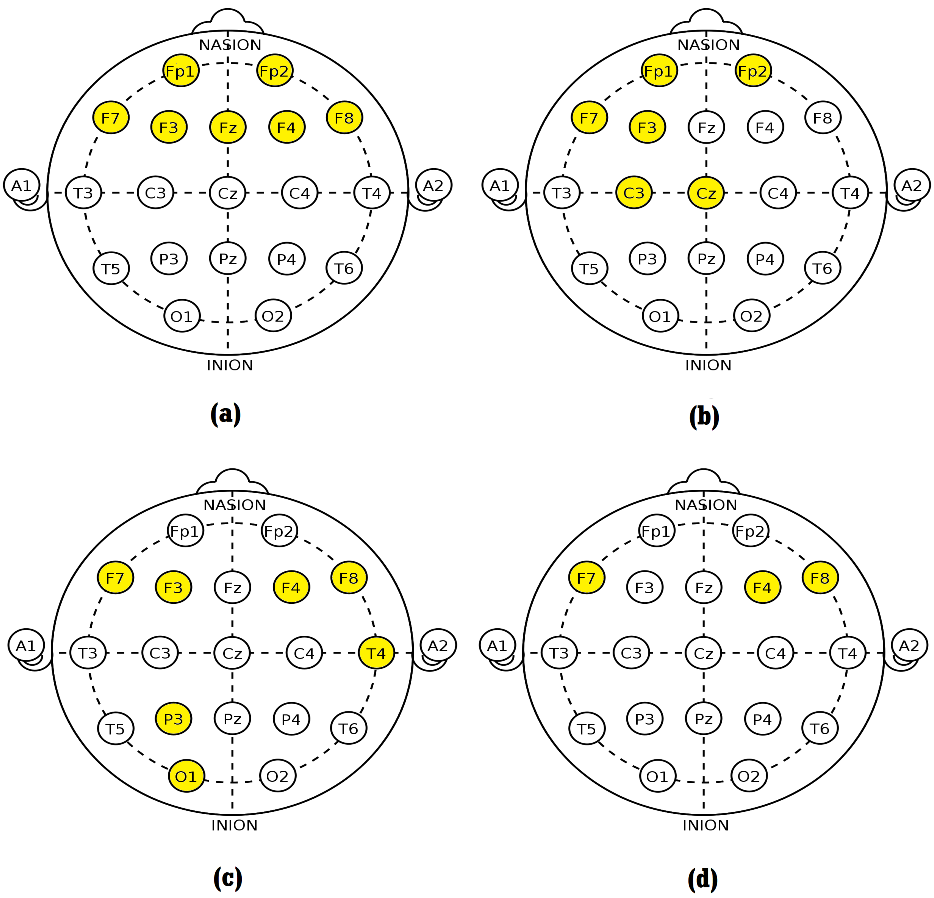

Figure 3: Best Electrodes Correlation Performance, highlighted in yellow colour: (**a**) Dataset 1 Correlation performance on pre-processed HRV and EEG, (**b**) Dataset 1 Correlation performance on pre-processed HRV and WT signals of EEG,(**c**) Dataset 2 Correlation performance on pre-processed HRV and EEG, (**d**) Dataset 2 Correlation performance on pre-processed HRV and WT signals of EEG.

Dataset 1-HRV & Wavelet Transformed EEG Correlation

EEG	HRV	Level 0	Level1	Level2	Level3	Level4	Level5
DELTA	LF	0.17	0.17	0.17	0.18	0.18	0.01
	HF	0.07	0.08	0.08	0.08	0.11	0.08
THETA	LF	0.04	0.04	0.01	0.07	0.17	0.03
	HF	0.07	0.08	0.07	0.03	0.15	0.03
ALPHA	LF	0.10	0.09	0.02	0.08	0.15	0.01
	HF	0.00	0.01	-0.01	0.01	0.10	0.00
BETA	LF	-0.01	-0.01	0.01	0.07	0.03	-0.05
	HF	-0.02	0.05	-0.02	0.03	0.07	0.01

Dataset 2-HRV & Wavelet Transformed EEG Correlation

EEG	HRV	Level 0	Level1	Level2	Level3	Level4	Level5
DELTA	LF	0.00	0.00	0.00	0.00	0.01	0.01
	HF	0.05	0.05	0.02	0.01	0.00	0.06
THETA	LF	-0.04	-0.05	-0.05	-0.04	0.02	0.08
	HF	0.00	-0.01	0.00	0.01	0.10	0.13
ALPHA	LF	-0.05	-0.06	-0.05	-0.02	0.03	0.11
	HF	0.04	0.03	0.04	0.00	0.16	0.13
BETA	LF	-0.06	-0.07	-0.08	-0.02	0.03	0.02
	HF	0.04	0.04	0.04	0.02	0.16	0.11

Table 4: Heat Map Results of Averaged participants correlation performance: Dataset 1 (Left), and Dataset 2 (on Right). Colour coding from Red to Dark Blue, Red=Strongest, Dark-Blue=Weakest)

In summary, the number of EEG electrodes used by other people to investigate correlation was limited. Our results cover a gap in the research concerning the correlation between the EEG and the HRV using all EEG electrodes. Our work suggests a correlation between the frontal lobe of the EEG and the HRV, with and without WT signals. We assume this is because the frontal lobe is related with higher mental functions of cerebral cortex and responsible for muscle movements of the body (Stuss and Benson, 1986).

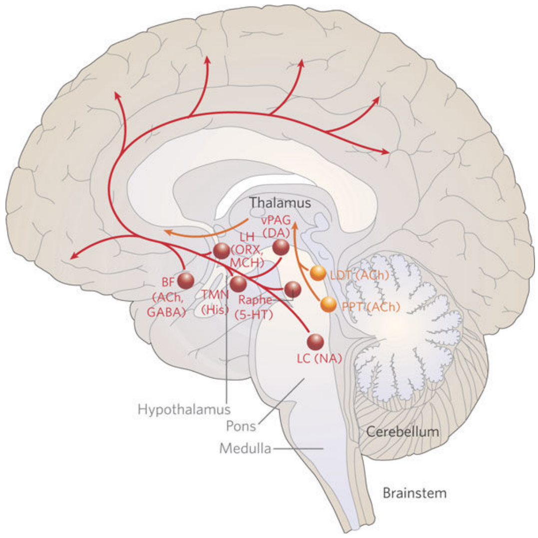

Figure 4: Key neuronal projections that maintain alertness, and possibly the path from cardiovascular center to the frontal lobe of the barin's communication. The figure is obtained from (Saper et al., 2005).

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