CONTINUOUS TIME QUANTIFICATION OF ATTENTION FROM SPARSE AND LIMITED REACTION RESPONSES RANDOMLY ACQUIRED IN TIME

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Abstract

One of the most used vigilance tests is the psychomotor vigilance test, known by its sensibility to fatigue. However, the test only allows getting accurate information in a limited time basis and requires full commitment of the user, making it not optimal for continuous monitoring. Therefore, in order to overcome these limitations this thesis deals with the problem of quantifying readouts of attentional processes in a continuously basis. A mathematical formulation for estimating readouts of attention is proposed using only limited reaction responses distributed randomly in time. The relation between encephalography's metrics and attention is one of the most reviewed in the literature. An experiment was designed to evaluate if the encephalography's metrics related to attentional processes can be modelled by limited reaction responses. Recruited volunteers performed the main task, a TETRIS game with embedded reaction tests, and simultaneous acquisition of encephalogram at the Institute of Systems and Robotics. Features related to gamma and alpha band are the optimal ones to be modelled by the reaction times, achieving medium/strong correlation ($p<0.05$) between the estimation and their value. The TETRIS framework showed potential to be a possible attention test and not just a means to achieve validation of the proposed mathematical formulation for vigilance monitoring. Feature extraction techniques based on control theory are proposed to extract relevant characteristics from time dynamics of the output estimation of the power of low gamma band. Lastly, the obtained results and limitations are discussed and possible future work is proposed.
Keywords: Attention, Continuous Reaction Times, Encephalogram, TETRIS, Feature Contenders, Kalman Filtering

1. INTRODUCTION

Different activation states of the cerebral cortex impact the ability to process information in our daily life. The scientific community has been using terminologies like alertness, vigilance and attention over the years. These terminologies are used differently in distinct scientific fields and scopes, making a general and accepted definition of these concepts a difficult task (Oken, Salinsky, and Elsas 2006). Most models in the field consider alertness the higher-level attentional processes, where alertness is the organism's physiologic and behavioural to respond to any type of stimulation. Alertness can be divided in two categories: phasic and tonic alertness. Tonic alertness is the individual's responsiveness in long intervals (minutes to hours)(Degutis 2010). Phasic attention can be defined as an individual's momentary changes in responsiveness and receptivity to different stimulations (within milliseconds). (Degutis 2010; Oken, Salinsky, and Elsas 2006)(Sohlberg and Mateer 2001). Some attentional processes are listed:

Focused Attention (Orienting Attention) – It is related to the basic responsiveness to stimulation. It is closely linked to phasic alertness.

Sustained Attention **(**Vigilance) – It is the ability to preserve a consistent behavioural response during a continuous and repetitive activity. In these tasks, stimuli occur randomly and infrequently relative to the main task.

Selective Attention – It refers to the maintenance of attention under the presence of competing or distracting stimuli.

For matters of simplicity, in this paper the concept of attention will be interchangeable with selective/focused attention. The same is done between vigilance and long-term sustained attention (hours). In this work, short-term sustained attention (minutes) is considered outside the scope of vigilance and considered to be included in attention. When the concept of attentional processes is mentioned, it refers to the mechanisms listed above.

Thus, attention can be defined as the process by which we are able focus on behaviourally relevant information, to select and enhance specified information processing while suppressing the rest that is irrelevant to the goal in hand.

2. MOTIVATION

In nowadays society, there are several situations that can lead to impairment of attentional processes. The biggest contributors are the individual's levels of fatigue (mental, physical or psychological) and sleepiness. Research points that fatigue is most prevalent among long-distance truck drivers, being responsible for 20 to 30% of crashes involving commercial road vehicles in Europe and the United States. (World Health Organisation and Who 2004)(Boksem, Kostermans, Tops, & De Cremer, 2012). In aviation, pilots are subjected to long and unpredictable duty hours, insufficient sleep and multiple time zone changes. Fatigue is a major contributor to aviation accidents (Borghini et al. 2014)(Caldwell et al. 2009)(Petrilli et al. 2006).

Several studies point that understanding mechanisms of attention has the potential to give insights about cognitive disorders and attention deficits, such as Narcolepsy and Attention deficit hyperactivity disorder (ADHD) (Allahverdy, Nasrabadi, and Mohammadi 2011; Naumann, Bellebaum, and Daum 2006; Rieger, Mayer, and Gauggel 2003). Thus, there are several fields where quantification of attention and/or vigilance can bring important contributions. It is in field of quantification of attentional processes this paper is focused on.

3. CONTINUOUS REACTION TIMES

Psychomotor vigilance test (PVT) is one common tool to tackle vigilance deteriorations. It is a computerized reaction time task that measures vigilance by recording response times (RT) to visual (or auditory) stimuli that occur at random inter-stimulus intervals. For example, PVT has been used to evaluate pilot's sustained attention, performing the test a few times during the task's duration. However, it has limitations. It requires full engagement of the subject to perform the PVT test, imposing an execution interruption of the main task, such as driving and piloting. Despite providing accurate and valuable information, the test only provides information in a short time window that corresponds to its duration.

These two limitations make the PVT not suitable for continuous fatigue monitoring, especially in critical tasks. Therefore, the main objective of this paper is to develop a minimum intrusive approach of vigilance quantification through sparse and non-uniform time distributed reaction stimuli responses. In this approach, a subject has to react occasionally to stimuli while performing his/her main task. This methodology allows the subject to maintain its primary task while continuously quantify the levels of tonic alertness. The price to pay is a higher variance/uncertainty on each measurement when compared to traditional PVT. The overall accuracy is improved by taking into account all measurements under the adoption of smooth constraints for the vigilance levels across time. In other words, there is a trade-off between information resolution (degree of accuracy of each measure) and time resolution (time window of available data). A mathematical formulation to estimate readouts of attentional processes (vigilance, selective attention, etc.) is proposed using only continuous reaction times (CRT). This way the main drawback of the proposed sampling methodology, the degree of accuracy of each measurement (reaction time), is overcome. This estimation problem was formulated using Kalman filtering, where the variance of the noisy continuous reaction times (CRTs) is minimized in order to model attentional processes (target variable), *Figure 1* and *Figure 2*.

Figure 1 – Schematic of the process of estimating attentional processes using only limited reaction times

An experimental design is built to validate the mathematical formulation. This procedure is based on a TETRIS game. The game simulates a general task where attention is requested, simulating workers in high attention demand tasks. During the game, and without having to stop it, the subject responds to random stimulus embedded in the game. As the main goal of this paper is to validate the potential of the mathematical formulation to estimate attentional processes and because vigilance tasks are not simple to design, an experiment was built to measure attention.

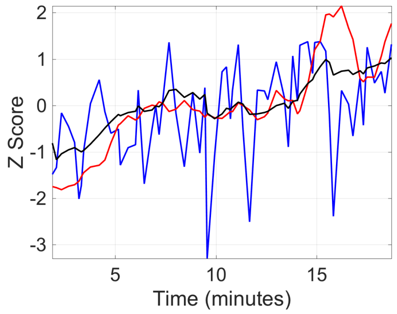

Figure 2 – Representation of the estimation problem dealt in the thesis. The limited and noisy reaction times (blue curve) are used to estimate the time dynamics of readouts of attentional processes (red curve). In black it is represented the estimation output.

As Encephalography is one of the electrophysiological signals most related to attention, EEG metrics are used as target variable for KF estimation.

4. EEG AND RELATIONSHIP TO ATTENTION

EEG is generally defined as electrical activity of an alternating type recorded from the scalp surface, subdurally or in the cerebral cortex (Teplan 2002). The fluctuations of the recorded electrical activity can be spectrally analysed in different standard EEG bands: Delta (δ), Theta (Θ), Alpha (α), Beta (β) and Gamma (ɣ). Literature reportes the involvement of some of these bands in attentional processes, but alpha and gamma band are the most consensual in the scientific community.

4.1. Alpha Band

Alpha activity occurs in the frequency range from 7 Hz to 14 Hz. It has been reported lower amount of alpha activity in higher attention demand tasks, while higher alpha activity is associated with signs of fatigue and sleepiness (Borghini et al. 2014)(Voytek et al. 2010). One of the most essential components in attention is the availability of cortical resources for task-relevant processes. The inhibition of non-relevant stimulus is crucial to not compromise task performance and to facilitate these task relevant processes. Neurophysiological systems achieve this inhibition of irrelevant task processes through alpha synchronization in cortical areas not relevant for the role in hand. Alpha synchronization has been consistently correlated with inhibition of task-irrelevant sensory areas (Mazaheri and Picton 2005) (Doesburg et al. 2008)(Clayton, Yeung, and Cohen Kadosh 2015)(Lopes da Silva 2013). For example, if auditory or somatosensory attention is required, these areas express alpha desynchronization, while the visual cortical area express higher alpha activity. Similarly, if visual attention is demanded, alpha desynchronization is expressed in cortical areas that demand visual processing, while auditory and somatosensory areas show alpha synchronization. In a recent review, it is stated that alpha phase also plays an important role in modulating information processing, where the phase of the alpha rhythm can reliably predict the detection of upcoming visual stimuli. Furthermore, it stresses that higher alpha activity power promotes the inhibition of cortical excitability (Lopes da Silva 2013). Other alpha related metrics have been suggested. High coupling between posterior gamma amplitude and anterior alpha phase is associated with an improvement in error detection, task accuracy and lower mental fatigue (Voytek et al. 2010) (Cohen and Van Gaal 2013).

4.2. Gama Band

Gamma oscillations occur in the frequency range approximately 30–100 Hz. Gamma rhythms are suggested to represent the rhythmic synchronization of different populations of neurons together with the goal of carrying out cognitive functions, such as working memory and attention. Indeed, it is believed the gamma oscillations are closely linked to the activation of task relevant cortical areas (Kahlbrock et al. 2012)(Müller, Gruber, and Keil 2000)(Herrmann, Munk, and Engel 2004). Gamma synchronization leads to faster response times and accuracy in visuospatial tasks. Literature also points higher gamma activity promotes visual attention processes, for example: orientation discrimination and shape-tracking (Taylor-Phillips et al. 2015)(Gregoriou et al. 2014) Moreover, findings show the lateral pre frontal cortex (LPFC) has an intimate connection with gamma activity in the visual cortex. Similarly, gamma power in auditory areas is increased during extended auditory attention tasks. Furthermore, it is suggested that if multiple visual features are competing for attention allocation, the attended one gets a competitive advantage over the rest by gamma band synchronization (Fries et al., 2001, 2008). (Clayton, Yeung, and Cohen Kadosh 2015)

5. MATHEMATICAL FORMULATION TO ESTIMATE READOUTS OF ATTENTIONAL PROCESSES

A mathematical formulation is proposed to minimize the variance of the measurements of CRT using Kalman Filtering (KF). The chosen formulation is a constant acceleration Kalman estimator, where EEG metrics are modelled as a physical particle that follows motion equations with *n* states and *m* measurements. The state-space model of the system (EEG's metrics position, velocity and acceleration) can be expressed as in equation 1:

$$\boldsymbol{x} = \begin{bmatrix} x \\ \dot{x} \\ \ddot{x} \end{bmatrix} \quad (1)$$

The KF model assumes the true state ($\boldsymbol{x}$) at time *k* is evolved from the state at ($k - 1$) according to equation 2.

$$\boldsymbol{x}_{k+1} = \boldsymbol{F}_k \boldsymbol{x}_k + \boldsymbol{w}_k \quad (2)$$

$\boldsymbol{F}_k$ is the state-transition model, equation 3, modelled by a state transition matrix, *n x n* matrix, applied to the previous state space, $\boldsymbol{x}_{k-1}$. Δt represents the time difference between stimuli. The process noise, $\boldsymbol{w}_k$, is modelled by a probability distribution with normal distribution of mean zero and covariance matrix of $\mathbf{Q}_k$, equation 4.

$$\boldsymbol{F}_k = \begin{bmatrix} 1 & \Delta t & \frac{\Delta t^2}{2} \\ 0 & 1 & \Delta t \\ 0 & 0 & 1 \end{bmatrix} \quad (3)$$

$$\boldsymbol{Q}_k = q \begin{bmatrix} \frac{\Delta t^5}{20} & \frac{\Delta t^4}{8} & \frac{\Delta t^3}{6} \\ \frac{\Delta t^4}{8} & \frac{\Delta t^3}{3} & \frac{\Delta t^2}{2} \\ \frac{\Delta t^3}{6} & \frac{\Delta t^2}{2} & \Delta t \end{bmatrix} \quad (4)$$

The KF model assumes that the measurements $\boldsymbol{z}_k$ at time *k* results from the true state $\boldsymbol{x}_k$ according to equation 5.

$$\boldsymbol{z}_k = H_k \boldsymbol{x}_k + \boldsymbol{v}_k \quad (5)$$

$\mathbf{H}_k$ represents the observation model, modelled by the measurement emission matrix, *m x n* matrix, which transforms the state space at time *k*, $\boldsymbol{x}_k$ to the observation space $\boldsymbol{z}_k$. As the state space's derivatives are assumed to be directed observable, $\mathbf{H}_k$ is formulated as in equation 6.

$$H_k = [a \quad b \quad c] \quad (6)$$

The observation noise, $\mathbf{v}_k$, is modelled by a normal probability distribution with zero mean Gaussian white noise with covariance $\mathbf{R}_k$. As the only measurement is the CRTs, the measurement covariance matrix is a single value, equation 7.

$$\boldsymbol{R}_k = \sigma_r^2 \quad (7)$$

As a result, attention modulation ends up being an estimation problem. A total of seven parameters need to be estimated (vector *Θ*, equation 8), which include measurement and process noise, the initial state space, $\hat{x}_{0|0}$, the initial state covariance matrix, $\hat{P}_{0|0}$, and three coefficients of the observation space. The optimal parameters were optimized using Least Mean Error (LMS).

$$\boldsymbol{\theta} = [\hat{x}_{0|0} \quad \hat{P}_{0|0} \quad \sigma_r^2 \quad q \quad a \quad b \quad c] \quad (8)$$

6. METHODS

An experiment was designed where subjects perform a task with embedded continuous visual stimuli (TETRIS) and simultaneous acquisition of EEG.

6.1. Hypotheses

Three main assumptions were formulated
H1 - Some EEG features are more suited to be modelled by the CRT than others (Feature Contenders - FC);
H2 - The CRT can estimate the time dynamics of the FCs with statistical significance;
H3 - The CRT can estimate EEG's metrics related to mechanisms of attentional processes

6.2. Population

The experiment was performed in 14 healthy subjects (24.3 ± 3.6 years). The task was performed around 15 minutes. All subjects were male in order to reduce sample variance. None of the subjects had neuropsychiatric diseases, expect one who noise contaminated and was excluded of further analysis. Two of the readings are considered partial readings (Subject 1 and 2 with a time on task lower than 10 minutes), as the time of acquisition could not be the same as the others due to technical issues.

6.3. Acquisition

A 2 channel EEG was recorded (Fz and Pz channels – sampling frequency of 250Hz) with hardware from LASEEB (Laboratório de Sistemas Evolutivos e Engenharia Biomédica) at Instituto de Sistemas e Robótica (ISR). The acquisition platform was a polysomnography Sonolab 620C from Meditron. The reference electrode was placed in the back of the subject's earlobe. The ground electrode was placed in the subject's left mastoid. A sampling frequency of 250Hz was deployed to ensure the Nyquist Theorem. As few channels were used, it was not possible to apply sophisticated artefact rejection algorithms, such as independent component analysis. A simple threshold of 100uV was used to reject EOG, movement and EMG artefacts. No approach was followed to tackle possible artefacts from intracranial EMG, which overlaps with high frequency bands (Muthukumaraswamy 2013). Several authors suggest that the frontoparietal neuronal network is one of the major players in attention. Thus, it was decided to measure the cortical activity of the region with Fz and Pz channels (Corbetta and Shulman 2002; Greene and Soto 2014). The EEG files were recorded in SOMNIUM environment in EDF format in order to be imported and analysed in MATLAB. All TETRIS files are saved in an Excel file. The TETRIS game was played in a different computer in order to visualize of EEG signal simultaneously.

6.4. Feature extraction

Before the extraction of EEG's metrics, an initial pre-processing of EEG's raw signal was made using several signal processing tools. First, each recording was bandpass filtered with a 100^{th} order FIR filter of low cut-off frequency of 0.5Hz (avoid DC information) and high cut-off frequency of 45 Hz. Each of the 13 recordings were segmented in 2 seconds time duration with 50% overlap between them. Segments with amplitude over 100uV, it would be considered noise or EOG/movement artefact and excluded from posterior analysis as explained previously. Then, for each extracted window several features were obtained: Time domain – In this category, time domain metrics such as the Hjorth parameters, which include Activity, Mobility and Complexity, and fractal dimensions, Higuchi and Katz, were extracted; Time-frequency – Time frequency analysis was performed through STFT using EEG related features from the standard frequency bands (Delta, Theta, Alpha, Beta, lower Gamma), including spectral power, phase and band ratios. Moreover, characteristics from Alpha, Beta and Gamma sub-bands were considered. A total of 58 metrics (time and time-frequency domain) were extracted for each channel. Upper gamma of the EEG was not chosen for analysis because of not only the spectral leakage of 50Hz interference, but also as the spectral power of upper gamma is very low compared to other bands, if the ratio of Gamma power over noise is not optimal it can compromise the band's information. Therefore, all signals were filtered at 45 Hz.

6.5. Data mining strategy

A data mining feature selection was developed to validate H1. This strategy computes Pearson and Spearman correlation between the EEG features and the CRTs to compute a final score. Also, the cost of aligning the CRT and each of the EEG features is computed with dynamic time warping (DTW). The output of each of the 3 metrics is used to compute a qualitative score for each feature, where the minimum score is 1 and the maximum score is equal to the number of features. The final score of each metric is computed by summing each of the ranking scores. The features with the highest scores are the candidates for Kalman optimization (Feature Contenders - FCs). Kalman Filter assumes Gaussian noise for both measurements and state space and both update and prediction steps are ruled by linear equations. So, it is desirable to have a higher linear relationship between the CRTs and the EEG metrics, which is evaluated with Pearson coefficient. Using Pearson and Spearman may seem redundant but if non-linearities exist between the CRTs and the metrics of EEG, it can only tracked with Spearman coefficient. As none of these two can evaluate time delays, DTW is necessary. Higher DTW costs means the 2 sequences are more time delayed than sequences with lower cost. EEG metrics that have lower cost of aligning themselves with the CRT make the Kalman estimation easier because it lowers the dependence of the velocity and acceleration states. DTW formulation can be accessed in the indicated literature (Ratanamahatana and Keogh 2004).
The scores were calculated at the level of the population and not individual to ensure statistical significance for each correlation (843 degrees of freedom in population analyses). A simple example of this process is explained with 3 hypothetical features in order to make it more understandable for the reader:

Table 1 – Score of each feature for each category

	Feature 1	Feature 2	Feature 3
Pearson	1 (r_p = 0.2)	2 (r_p = 0.4)	3 (r_p = 0.7)
Spearman	1 (r_s = 0.25)	2 (r_s = 0.4)	3 (r_s = 0.7)
DTW	1 (cost =0.9)	2 (cost = 0.7)	3 (cost = 0.1)

In *Table 1*, each metric is computed between each feature and the CRT (r_s, r_p and cost). Then, a ranking is built for each resemblance metric (qualitative score between 1 and 3, where 3 the number of features). Each of these qualitative scores is summed as shown in *Table 2*.

Table 2 – Final Score of each feature of the example

	Feature 1	Feature 2	Feature 3
Final Score	1+1+1 = 3	2 + 2 +2 = 6	3 + 3 +3 = 9

In this example, if a threshold of 7 is chosen, only feature 3 is considered as a FC and chosen for Kalman estimation. The same procedure is used for two different analyses. For one hand, instead of 3 features, the procedure is adopted to the 58 EEG features extracted (maximum final score of 174). From the 58, the group with scores higher than 160 are considered as FCs for posterior Kalman estimation (Case 1). On the other hand, instead of 3 features, the procedure is also adopted across the frequency spectrum (45 features, each feature is 1 individual frequency from 1Hz to 45Hz). The goal is to understand if there is or not a spectral tendency of the scores. In order words, the three resemblance metrics are computed between the power of each individual frequency and the CRT. A cut-off threshold of the final score >100 is used to comprehend which frequency ranges are most relevant (Case 2).

6.6. Kalman Filtering

This step is essential to validate H2. The FCs are used as target variables of the Kalman Filter**.** Several performance metrics are computed to evaluate how the well the CRTs can model the optimal features: Pearson Correlation, Spearman Correlation and DTW between the Kalman estimation and the true EEG metric value (same as the previous section). FCs that achieve statistical significance are compared with the literature to evaluate if they are related to attentional processes or not. If yes, H3 is validated. The optimization of the seven parameters, vector ϴ in equation 8, is made through least mean square (LMS) for each FC. Cross validation strategy is adopted. Leave Out One Cross Validation Strategy is pursued where from N subjects, N-1 are used as training set for the Kalman Filter. The test set includes the individual that is not used in the training set. Also, a one-way Kruskal-Wallis test was conducted between the FCs (for each performance metric) to determine if the performance of one or more FC is statistically better than the others.

6.7. Feature extraction of the FCs

One of the FCs is chosen analysed in this section. As it will be shown in the results section, the chosen FC was low gamma power. Three strategies are proposed to extract relevant information of the estimated curve estimated gamma (output of Kalman estimation). However, as the sampling times between stimuli are unequal, time-frequency analysis is not feasible. The estimated curve is thus represented across the number of stimulus responded (CRT-domain instead of time-domain). In the CRT domain samples have the same interval between them and time frequency analysis is possible (CRT-frequency analysis). By evaluating visually different subjects, there are individuals who have a constant rise of estimated gamma, EG, (Subject 6 and 7 and 9) while others have a more oscillating behaviour (all others), which were named undamped and damped group respectively by this property. All proposed strategies have the goal of discriminating these two groups.

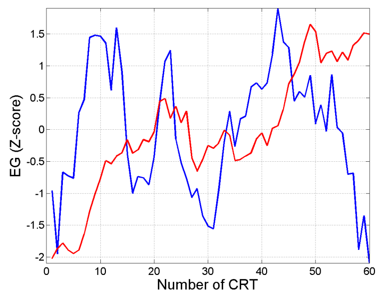

Figure 3 - Time evolution of the estimated gamma power (EG) of two subjects of two distinct groups (blue – Subject 3 – Damped group; red – Subject 6 – Undamped group

- **1st Strategy**

In this first strategy, for each individual, several metrics of the estimated curve of the chosen FC are extracted (6 at total). The population curve of the estimation of gamma power is displayed to exemplify the representation of each one, *Figure 3*. The population's time evolution dynamics is built according to the data's mean and standard deviation in the CRT domain.

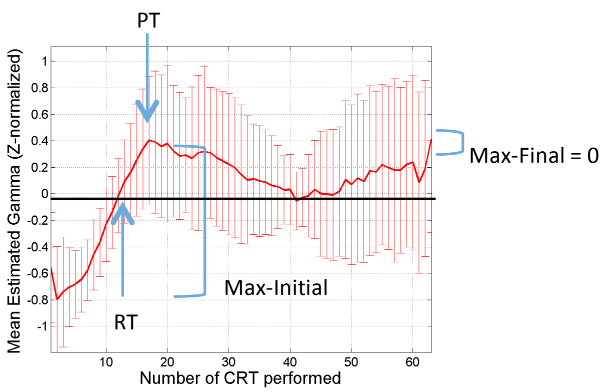

Figure 4 – Population curve in the CRT domain of the estimation of the optimal feature. 4 of 6 listed metrics are represented. Only ZCR and normalized peak time are not represented.

The six metrics include:
Rising time (RT) - Rising time corresponds to the time the signal crossed the y-axis for the first time. In other words, the first time the signal crosses its mean value if the signal is not z-normalized;
Peak time or Maximum time (PT or MT) - The peak time corresponds to the time the max value is achieved;
Zero Crossing Rate (ZCR) - The zero crossing rate corresponds to the ratio of number of times the signal crossed the y-axis over the number of CRT answered;
Difference between MaxValue and FinalValue - The difference between the maximum value of the signal and its value at the end;
Difference between MaxValue and InitialValue - The difference between the maximum and initial value of the signal;
Normalized peak/maximum time – Ratio between maximum time (feature 2) and number of CRT answered.

Before extraction of the six features, the data was Z-normalized to scale all signals to the same order. A two-way t-test was performed for each feature to determine if the any of these features is statistically different between the undamped and damped group. A scoring system was developed using principal component analysis (PCA). The features that rejected the null hypothesis were Z-normalized and used as input in PCA. The first principal component is selected and used as a scoring scale for undamped and damped subjects.

- **2nd Strategy**

In this second strategy, each estimated curve of estimated gamma is modelled through an AR-model (3rd degree). The coefficients were obtained by least mean square optimization. The AR-model of the signal is used to obtain its filter response. Phase response of the filter is computed for each subject. As the signal is discrete, the phase is represented from $-\pi$ to $+\pi$ (-180 and 180 degrees), *Figure 5*.

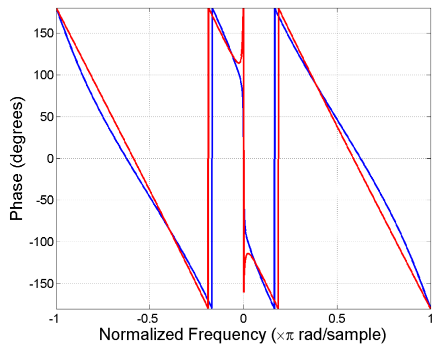

Figure 5 - Phase response. Undamped subject is represented in red while damped subject is represented in blue.

The sampling frequency of this CRT-frequency representation is 1 CRT^{-1} (the equivalent to Hz in time). The phase response of each subject is derived across frequency (phase velocity) to find once again characteristics to distinguish the undamped and damped group. If *P* is the phase response, its phase velocity (PV) is computed as followed:

$$PV = \frac{dP}{df} \tag{9}$$

As the red spike around 0 CRT^{-1} is most evident difference between the groups, *Figure 5*, the maximum and minimum value of the PV around lower frequencies of each subject is extracted. The PCA is applied using the two features of phase velocity as input. Just like strategy 1, the first principal component is used to build a scoring scale to distinguish both groups.

- **3rd Strategy**

The last mining strategy also involves the filter response of the AR-modelling. Instead of calculating the phase and magnitude response, the filter's poles were determined. As a 3rd degree model was chosen, every subject has three characteristic poles. Each pole's natural frequency (ω), damping ratio (ε) and time constant (τ) were computed. No statistical test was conducted.

7. RESULTS

7.1. Acquisition

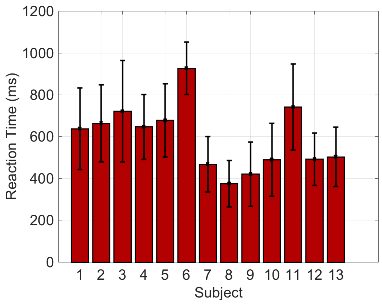

Figure 6 - Mean (red) and variance (black) of the reaction times of each subject (left).

A high inter subject variability of the reaction times was obtained - *Figure 6*. TETRIS is complex game, far more complex than other tasks because it largely depends of the skill of the player. While monitoring the subjects during the experiment, it was clear that the worst players were the ones that reacted slower to the visual stimuli and have higher reaction time variance. Players with more skill reacted more easily to the stimuli and their reaction times were more constant. This skill dependency contaminates the reaction times' statistics (mean and variance). As a result, it was decided that all data and analysis (correlations and estimations) should be Z-normalized to eliminate this skill dependency. It was decided to focus on analysing time-dynamics.

7.2. Data Mining Strategy

In this section, the main results of the proposed data mining strategy are presented. For each channel the FCs are determined. The correlations of each score obtained a $p<<0.01$. The top FCs of the 58 EEG features (score >160) are presented in Table 3 and Table 4. Scores from different channels are not comparable.

Table 3 – Major feature contenders of Pz channel (Score >160) and their respective ranking score. The scores of the other 54 features of the Pz are not present.

Major FC of Pz channel	Score (0-174)
Spectral Frequency	174
Low Gama PSD	169
Gama peak frequency	169
Katz Fractal	166

Table 4 - Major feature contenders of Fz channel (Score >160) and their respective ranking score. The scores of the other 53 features of the Fz are not present.

Major FC of Fz channel	Score (0-174)
Low Gama PSD/Alpha PSD	174
Higuchi Fractal	169
Low Gama PSD/(Beta PSD + Alpha PSD)	169
Normalized Low Gama PSD	164
Low Gama PSD/(Theta PSD + Alpha PSD)	164

By analysing Table 3 and Table 4, only a few EEG metrics achieved the status of FCs, 4 in Pz channel and 5 in the Fz channel. The rest are considered non-optimal features. This group of non-optimal features includes: the phase response of the different EEG bands and sub-bands; power spectrum density of lower frequencies, delta, theta and alpha bands; Hjorth parameters (Activity, Mobility and Complexity); normalized the power spectral densities of different bands besides gamma. These features were excluded from further analysis. Despite solo alpha power not being in the top features, it appears in the denominator of some FCs.
Most noticeably, power of low gamma and gamma related features obtained all high-ranking scores across both channels. In Fz channel, low gamma power and the frequency of highest gamma power (gamma peak) achieved 2nd and 3rd best places respectively, Table 3. In Pz channel, Table 4, 4 of the 5 FCs are features proportional to the power of Gamma. Both time domain fractal dimensions, Katz and Higuchi also showed promising results in Pz channel and Fz channel respectively. This top spot belongs to Spectral Frequency, Table 3.
Thus, these results show that H1 is validated because a group of EEG features stood out of the 58 extracted features, Table 3 and Table 4.
From this analysis, 5 metrics are common across the 9 FCs: low gamma power, fractal dimensions, spectral frequency, gamma peak frequency and alpha power. Spectral frequency is the frequency (Sf) that defines a frequency range from 0 Hz to Sf Hz, which includes 95% of the power spectrum density in a pre-determined time window. When referring to fractal dimensions, such as Katz and Higuchi, they try to estimate how complex a signal is. Also, gamma band has a narrow frequency band that presents much higher spectral power than the rest of its band. This characteristic region is called the gamma peak and generally surrounds the 40 Hz. If higher amplitude is present in the gamma peak region, gamma power is also higher.
Some findings are corroborated by the spectral tendency of the scores.

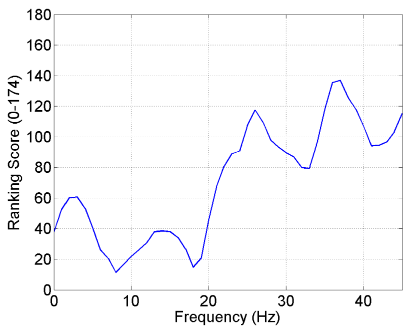

Figure 7 – Evolution of the ranking scores of non-normalized spectral power across frequency for Pz channel. The tendency to higher frequencies is evident. Fz is not displayed.

The ranking scores of the spectral evolution displayed in Figure 7. These scores are much lower than the top scores of the 58 features per channel, Table 3 and Table 4, because the maximum score of this spectral evolution analysis is 135 (45 times 3). In the CRT analysis, the results of the optimal FCs, Table 3 and Table 4, are coherent with the rankings scores across the frequency spectrum, Figure 7. A clear tendency exists where higher scores correspond to higher frequencies (Figure 7 - blue line), especially in the gamma band. H1 was validated, the FCs (9 features) are selected for the next round of analysis.

7.3. Kalman Filtering

In this sub-section, the results of applying the mathematical formulation to estimate readouts of attention are presented. 9 EEG features were selected as FC in the previous section. In this sub section, a Kalman filter model is trained for each FC to evaluate if the CRT can model its time dynamics. (Cross validation strategy) The performance metrics of these estimations are computed to evaluate statistical significance of the estimation and if any feature stands out of the rest. The graphic result of the performance of the estimated is only presented for low parietal gamma power, *Figure 8*.

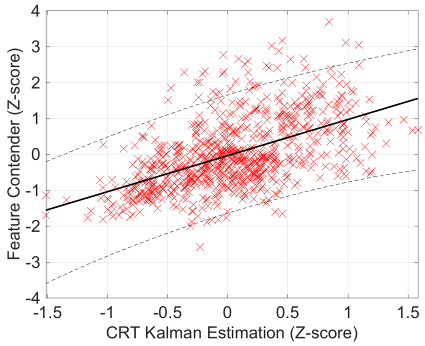

Figure 8 - Kalman estimation of Pz low gamma power. The cloud of points of the experimental data is displayed alongside with the confidence intervals (95%). Notice the high variance across the estimation

Table 5 –Pearson and Spearman correlation, and DTW performance metrics for the 4 FCs of the Pz channel. All correlations have a p-value<0.05.

FC	Pearson Correlation	Spearman Correlation	DTW
Spectral Frequency	0,477 ±0,285	0,445 ± 0,292	33,97 ±16,2
Low Gama Power	0. 598±0,249	0. 558±0,267	31,4 ±16,03
Gama peak frequency	0. 590±0,259	0. 559±0,274	32,6 ±16,11
Katz fractal	0. 491±0,358	0.552±0,379	37,5 ±21,36

Table 6 - Pearson and Spearman correlation and DTW performance metrics for the 4 FCs of the Fz channel. All correlations have p<0.05.

FC	Pearson Correlation	Spearman Correlation	DTW
Gama/Alpha	0. 54 ± 0,22	0.54 ±0,23	33,11 ±15,44
Higuchi Fractal	0.519 ± 0,32	0.468 ±0,30	35,24 ±18,02
Gama/ (Beta+Alpha)	0. 549 ± 0,10	0.55 ±0,197	34,00 ±15,60
Normalized Gama power	0.50 ± 0,27	0.47 ±0,245	35,99 ±17,988
Gama/ (Theta+Alpha)	0. 52 ± 0,27	0.47± 0,286	36,49 ±18,51

All FCs obtained medium or medium/strong correlation (p-value<0.05) between their true value and their estimation using Kalman Filtering and CRT as its input. However, it is noticeable the high variance of the performance metrics across the FCs, representing the high inter subject variability - *Figure 8*, *Table 6* and *Table 5*. A Kruskal-Wallis test was conducted for each performance metrics to determine if any FC is statistically different from the others (H1). The null hypothesis was not rejected in any performance metrics.
Therefore, It is concluded there is no optimal EEG feature that outstands the others. Also there is no preferable channel where the estimation is better.

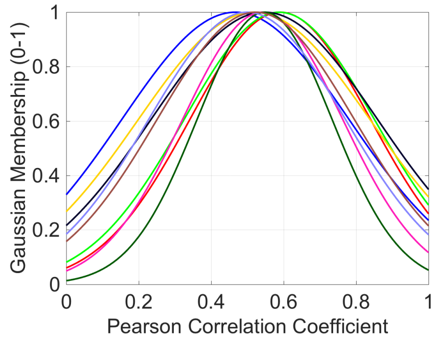

Figure 9 - Gaussian distribution of the Pearson correlation between each FC and their estimated value 9 FCs (the other performance metrics are not displayed). No clear distinction exists between them.

DTW revealed itself not very useful at this stage. In DTW's cost, all results have a similar mean value and high variance, *Table 5* and *Table 6*. A constant acceleration (CA) Kalman Filter was used in this work. As mentioned before, CA can track rapidly changing oscillations and eliminate time delays between the input and target variable. This could have made the DTW not so helpful as a metric judge. It is concluded that the CRT can model each of the FCs with medium or medium/strong correlation (p<0.05), validating the H2. This aspect is crucial because the proposed data mining strategy can only tell us which features better than others. Despite these being better, they could have been bad overall.
Two FCs are Katz and Higuchi. However, very little literature was found connecting fractals to attentional processes. Gamma frequency peak is one of the FCs. Also, little findings show the connection between frequency shifts of the Gamma peak and attentional processes. In the literature two of the frequency bands more connected to attention are gamma and alpha band. For one hand, gamma activity has been linked with selective attention and continuous activation of task relevant cortical areas. This connection has been found in several different types of studies including feature and spatial attention and lesion studies (Doesburg et al. 2008; Fell et al. 2003; Kahlbrock et al. 2012; Kim et al. 2015). On the other hand, alpha activity inhibits irrelevant task processes in cortical areas not relevant for the role in hand. Alpha synchronization has been consistently correlated with inhibition of task-irrelevant sensory areas (Mazaheri and Picton 2005) (Doesburg et al. 2008)(Clayton, Yeung, and Cohen Kadosh 2015)(Clayton, Yeung, and Cohen Kadosh 2015)(Lopes da Silva 2013). Thus, H3 is validated.

7.4. Feature Extraction of the FCs

An effort was put to develop possible methodologies that can extract interesting metrics of the time dynamics of the FCs related to gamma or alpha bands. The proposed feature extraction techniques were only applied to low parietal gamma power. Analysing the population curve of estimated gamma (*Figure 4*), some interesting conclusions can be drawn by the population's line of tendency and variance across the different zones (error bars): a constant rise of gamma in the beginning of the experiment (0 to 15 CRT); the existence of a gamma peak (15 to 20 CRT); a slow decrease during 20 CRT; plateau during the rest of the experiment.

- **Strategy 1**

Four of the six extracted metrics in strategy 1 are not statistically different from one group to the other, *Figure 10*. Only Normalized MT and the variation between final and initial value of the signal rejected the null hypothesis (p<0.05). As the number of subjects is low, high T values cannot be obtained.

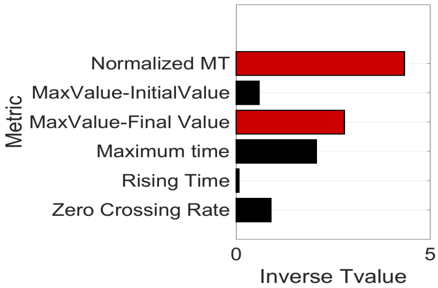

Figure 10 – Two-way t-test between the undamped and damped group. Features that are significantly different (red) and features that the null hypothesis was not rejected (black) are represented

By analysing the elements of each group, *Figure 3*, and the characteristics of each subject, *Figure 11*, interesting conclusions can be drawn. If an individual has a constant rise of estimated gamma, his maximum value will be close to the end of the experiment. In an oscillatory signal, the maximum can appear in any time. For one hand, undamped subjects have peak time near the end of the experiment and a small difference between the Max and Final value of the signal (anti correlation between features). On the other hand, the damped group can have a final signal value much more different than an undamped subject.

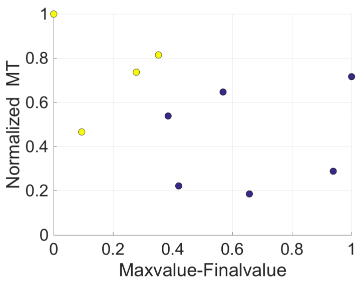

Figure 11 - Cloud of points representing the 2 features that rejected the null hypothesis (Yellow – Undamped, Blue - Damped)

These two features used to build the PCA score. This score generated a smooth score trend, as displayed in *Figure 12*. Subjects from the undamped group (6, 7, 9 – red bars) achieved score above 0.6. Notice that this score misplaces subject 4, who belongs to the damped group.

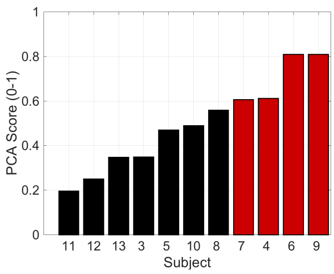

Figure 12 – PCA score of the eleven subjects using the CRT domain features. The subjects with lower score (black) have an oscillatory attention while subjects with higher scores (red) have a constant increase of attention during the experiment.

- **Strategy 2**

In the 2nd strategy, features are extracted from the phase response of the filter response, *Figure 5*, which was computed from the AR-model of the estimated gamma. Subjects from the undamped and damped group have substantial differences in their phase velocities in very low frequencies - *Figure 13*. However, Their phase velocity in intermediate and higher frequencies is similar across different subjects. Thus, the phase velocity allowed to conclude that the amplitude range of both groups' phase velocity in lower frequencies is substantial different (higher maximum and lower minimum), as shown in Figure 13.

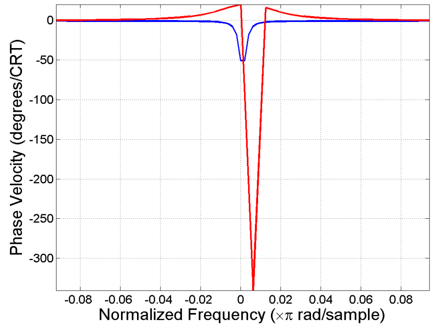

Figure 13 – Phase response (left) and phase velocity (right) results from one sample of each group. Undamped subject is represented in red while damped subject is represented in blue.

Lower minimum phase velocity and higher maximum phase velocity characterize the cluster of subjects belonging to the undamped group (blue cluster in *Figure 14*), where higher minimum phase velocity and lower maximum phase velocity characterize the cluster of subjects belonging to the damped group (red cluster in the bottom right of *Figure 14*).

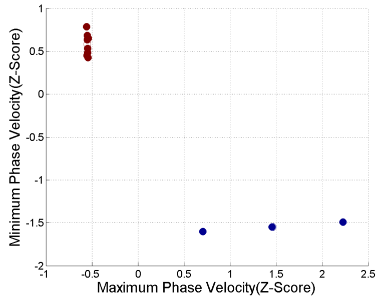

Figure 14 – Z-score normalized feature representation of both extracted metrics from phase velocity (left), where damped subjects are represented in the red and undamped in blue. PCA eigenvalues of the extracted features (right).

Higher distinguishability was obtained in this PCA scoring, *Figure 15*. Better than the 1st strategy. Also, the subjects are not misplaced like in strategy 1.

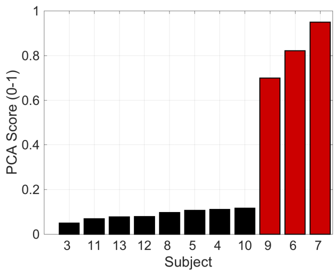

Figure 15 – Sorted PCA score of the eleven subjects after feature reduction using the Phase Velocity features. The subjects with lower score (black) have an oscillatory attention while subjects with higher scores (red) have a constant increase of attention during the experiment.

Substantial distinguishability is achieved between both groups, in *Figure 15*. Thus, undamped subjects obtain high scores, between 0.6 and 1. On the contrary damped subjects obtain very low scores, below 0.1. Despite statistical tests were not performed to confirm this (low number of subjects), it is believed this technique can effectively discretize these two groups.

- **Strategy 3**

Strategy 3 focused on each subject's poles. The closest pole (CP) to the unitary circle of the filter response showed the most potential to distinguish the undamped group from the rest. The other poles farther from the unitary circle did not relevant insights. The damping ratio (ε) between groups is highly discriminative, where all subjects from undamped group have negative ε, while all subjects from the damped group have a positive ε - *Table 7*. It is concluded ε is an automatic tool to distinguish these two groups. No substantial differences were found studying the pole's natural frequency or conjugate complex poles, but more statistical analyses should be made to confirm it.

Table 7 - Damping Ratio of three poles of each subject as a result of the autoregressive estimation of lower parietal gamma

Subject	ε (closest pole)
3	1
4	1
5	1
6	-1
7	-1
8	1
9	-1
10	1
11	1
12	1
13	1

7. DISCUSSION

This paper proposes a methodology of quantifying tonic alertness/vigilance using only sparse reaction times distributed randomly in time (CRT). Despite, the experimental design was more directed to attention than the field of vigilance, the main goal and contribution of the thesis was the validation of the potential of the mathematical formulation for estimating attentional processes using the CRT. The proposed formulation was able to model the time dynamics of features related to two EEG bands with medium/strong correlation ($p<0.05$). These EEG bands are recognized to be related to attentional processes: gamma and alpha band. These have been linked to the enhancement of task relevant processes and inhibition of irrelevant task processes, which are two components of attention.

Despite fractals (Katz and Higuchi) and gamma peak frequency achieved statistical significance, little literature has linked them to attentional processes. No optimal feature stood out of the group in performance, as no statistical difference was achieved between them. The 1st data mining strategy was able to separate partially undamped and damped groups. However, a strong distinguishability was not achieved. The poles' characteristics provide the best discrimination of the 3 strategies, being an automatic decision tool.

This work presents several limitations in the acquisition. One of the most important steps in EEG research is noise and artefact removal so that the quality of data and proper conclusions could be drawn. Generally, a high number of channels is used in EEG's experimental design. This way it is possible to apply sophisticated signal processing techniques, such as Independent Component Analysis and Laplacians to remove any unwanted signal including EOG, EMG and movement artefacts. The only available hardware was composed of only 2 channels so these algorithms could not be applied. Intracranial EMG may interference with analyses in high frequency bands.

At the acquisition level, another way to increase robustness is to record EEG during five minutes before the beginning of the task to serve as baseline. As one of the initial goals was to be able to track EEG oscillations, it was not taken in consideration the importance of this period of time, which can give substantial insights for feature extraction, mainly in how for example low gamma power rises in the beginning of the experiment.

It is believed higher gamma activity makes the subject more focused in the task in hand (playing the TETRIS game). Higher focused/orienting attention makes the subject more vulnerable responding to the distracting stimulus, leading to an increase in reaction times. This conclusion seems contra intuitive as generally low response times correspond higher attention levels, such as in PVT. This is justified because PVT and the TETRIS game try to quantify different attentional processes. PVT measures tonic alertness where the subject has to respond as quickly as possible to a task-relevant stimulus. The CRT-TETRIS game tries to measure focused/selective attention and short-term sustained attention, where the subject has to respond to the non-relevant task stimulus as quickly as possible while maintaining attention at the main task. TETRIS was originally developed for the validation the mathematical formulation of attentional processes but the electrophysiological findings show that CRT-TETRIS can be a potential attention test for neuropsychiatric disorders where attention deficits are evident, such as ADHD and Narcolepsy. The CRT-TETRIS is able to model with medium/strong correlation a group of features that are related to gamma and alpha band, which have been linked to several attention studies. This game based framework is one of the thesis greatest contributions. It is true several focused and selective attention tests exist but CRT-TETRIS brings some advantages and advances in the field of attention. Most vigilance or attention tests use metrics that don't consider the test's time dynamics, such as the PVT. The combination of the mathematical formulation the control based feature extraction techniques can bring to the table new features and insights that are not currently explored. Despite TETRIS complexity may seem a disadvantage, it be turned into one of its major advantages. It is hypothesized that if some attentional processes can de modelled in such a complex environment using only one input, this can be also done in other similar tasks, such as other task driven games. In addition, as it is game based, it is more appealing for children.

8. CONCLUSIONS AND FUTURE WORK

Despite the initial motivation was in the field of vigilance, most of work and electrophysiological findings were in the field of attention, more concretely in focused/selective attention and short term sustained attention. However, contributions of the thesis can be applied to both vigilance and attention. But first, the limitations of this work should be tackled to improve what was done. The acquisition limitations must be overcome to evaluate the potential threat of the intracranial EMG contaminating the gamma band. Moreover, the new set of experiments should be focused on improving: subject diversity (age and gender), number of channels (especially including Oz for visual attention and Fp1 and Fp2 for EOG recording and artefact rejection), ECG recording for evaluation of the parasympathetic and sympathetic autonomic activity, and inquiries about sleep habits. This suggestion is already being taken place at the clinic: Centro do Sono Teresa Paiva in Lisbon. Only then, a more ambitious work can be pursued.

For one hand, the potential of the mathematical formulation for attentional processes was proven and therefore, one option is to apply it in a new experimental design with the objective of building a continuous tonic alertness monitor to evaluate fatigue. On the other hand, the mathematical formulation to estimate attentional processes and electrophysiological findings of the experimental design can be more deeply explored in the field of attention. It is believed the thesis opens new doors to explore the CRT-TETRIS as a potential focused attention test. This framework can estimate features related to gamma band and alpha band with medium/strong correlation ($p<0.05$). By hypothesis, these estimations can be used "offline" to evaluate and diagnose neuropsychiatric disorders related to attention deficits, such as ADHD or narcolepsy. The thesis offers three feature extraction techniques of these estimations as possible methodologies (not validated) to perform this evaluation. One possible direction is to design a new set of experiments to validate or not if it can distinguish between groups of control and groups with attention deficits.

9. REFERENCES

Allahverdy, a., Ali Moti Nasrabadi, and Mohammad Reza Mohammadi. 2011. "Detecting ADHD Children Using Symbolic Dynamic of Nonlinear Features of EEG." *2011 19th Iranian Conference on Electrical Engineering* (September 2015): 1–1.

Borghini, Gianluca et al. 2014. "Measuring Neurophysiological Signals in Aircraft Pilots and Car Drivers for the Assessment of Mental Workload, Fatigue and Drowsiness." *Neuroscience and Biobehavioral Reviews* 44: 58–75. http://dx.doi.org/10.1016/j.neubiorev.2012.10.003.

Caldwell, John a. et al. 2009. "Fatigue Countermeasures in Aviation." *Aviation Space and Environmental Medicine* 80(1): 29–59.

Clayton, Michael S., Nick Yeung, and Roi Cohen Kadosh. 2015. "The Roles of Cortical Oscillations in Sustained Attention." *Trends in Cognitive Sciences* 19(4): 188–95. http://linkinghub.elsevier.com/retrieve/pii/S1364661315000285.

Cohen, Michael X., and Simon Van Gaal. 2013. "Dynamic Interactions between Large-Scale Brain Networks Predict Behavioral Adaptation after Perceptual Errors." *Cerebral Cortex* 23(5): 1061–72.

Corbetta, Maurizio, and Gordon L Shulman. 2002. "Control of Goal-Directed and Stimulus-Driven Attention in the Brain." *Nature reviews. Neuroscience* 3(3): 201–15.

Degutis, Joseph M. 2010. "Tonic and Phasic Alertness Training: A Novel Behavioral Therapy to Improve Spatial and Non-Spatial Attention in Patients with Hemispatial Neglect." *Frontiers in Human Neuroscience* 4(August): 1–17. http://journal.frontiersin.org/article/10.3389/fnhum.2010.00060/abstract.

Doesburg, Sam M., Alexa B. Roggeveen, Keiichi Kitajo, and Lawrence M. Ward. 2008. "Large-Scale Gamma-Band Phase Synchronization and Selective Attention." *Cerebral Cortex* 18(2): 386–96.

Fell, Juergen et al. 2003. "Is Synchronized Neuronal Gamma Activity Relevant for Selective Attention?" *Brain Research Reviews* 42(3): 265–72.

Greene, Ciara M., and David Soto. 2014. "Functional Connectivity between Ventral and Dorsal Frontoparietal Networks Underlies Stimulus-Driven and Working Memory-Driven Sources of Visual Distraction." *NeuroImage* 84: 290–98. http://dx.doi.org/10.1016/j.neuroimage.2013.08.060.

Gregoriou, Georgia G, Andrew F Rossi, Leslie G Ungerleider, and Robert Desimone. 2014. "Lesions of Prefrontal Cortex Reduce Attentional Modulation of Neuronal Responses and Synchrony in V4." *Nature neuroscience* 17(7): 1003–11. http://www.ncbi.nlm.nih.gov/pubmed/24929661.

Herrmann, Christoph S., Matthias H J Munk, and Andreas K. Engel. 2004. "Cognitive Functions of Gamma-Band Activity: Memory Match and Utilization." *Trends in Cognitive Sciences* 8(8): 347–55.

Kahlbrock, Nina, Markus Butz, Elisabeth S. May, and Alfons Schnitzler. 2012. "Sustained Gamma Band Synchronization in Early Visual Areas Reflects the Level of Selective Attention." *NeuroImage* 59(1): 673–81. http://dx.doi.org/10.1016/j.neuroimage.2011.07.017.

Kim, Jun Won et al. 2015. "Theta-Phase Gamma-Amplitude Coupling as a Neurophysiological Marker of Attention Deficit/hyperactivity Disorder in Children." *Neuroscience letters* 603: 25–30. http://www.sciencedirect.com/science/article/pii/S0304394015300264.

Lopes da Silva, Fernando. 2013. "EEG and MEG: Relevance to Neuroscience." *Neuron* 80(5): 1112–28. http://linkinghub.elsevier.com/retrieve/pii/S0896627313009203.

Mazaheri, Ali, and Terence W. Picton. 2005. "EEG Spectral Dynamics during Discrimination of Auditory and Visual Targets." *Cognitive Brain Research* 24(1): 81–96.

Müller, M M, T Gruber, and a Keil. 2000. "Modulation of Induced Gamma Band Activity in the Human EEG by Attention and Visual Information Processing." *International journal of psychophysiology : official journal of the International Organization of Psychophysiology* 38(3): 283–99.

Muthukumaraswamy, Suresh D. 2013. "High-Frequency Brain Activity and Muscle Artifacts in MEG/EEG: A Review and Recommendations." *Frontiers in human neuroscience* 7(April): 138. http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3625857&tool=pmcentrez&rendertype=abstract.

Naumann, a, C Bellebaum, and I Daum. 2006. "Cognitive Deficits in Narcolepsy." *Journal of sleep research* 15(3): 329–38. http://www.ncbi.nlm.nih.gov/pubmed/16911036.

Oken, B. S., M. C. Salinsky, and S. M. Elsas. 2006. "Vigilance, Alertness, or Sustained Attention: Physiological Basis and Measurement." *Clinical Neurophysiology* 117(9): 1885–1901.

Petrilli, Renée M., Gregory D. Roach, Drew Dawson, and Nicole Lamond. 2006. "The Sleep, Subjective Fatigue, and Sustained Attention of Commercial Airline Pilots during an International Pattern." *Chronobiology International* 23(6): 1357–62. http://www.tandfonline.com/doi/full/10.1080/07420520601085925.

Ratanamahatana, Ca, and E Keogh. 2004. "Everything You Know about Dynamic Time Warping Is Wrong." *Third Workshop on Mining Temporal and Sequential Data*: 22–25. http://spoken-number-recognition.googlecode.com/svn/trunk/docs/Dynamic time warping/DTW_myths.pdf.

Rieger, Martina, Geert Mayer, and Siegfried Gauggel. 2003. "Attention Deficits in Patients with Narcolepsy." *Sleep* 26(1): 36–43. http://www.ncbi.nlm.nih.gov/pubmed/12627730.

Sohlberg, M M, and C a Mateer. 2001. "Improving Attention and Managing Attentional Problems. Adapting Rehabilitation Techniques to Adults with ADD." *Annals of the New York Academy of Sciences* 931: 359–75.

Taylor-Phillips, Sian et al. 2015. "Retrospective Review of the Drop in Observer Detection Performance Over Time in Lesion-Enriched Experimental Studies." *Journal of Digital Imaging* 28(1): 32–40. http://link.springer.com/10.1007/s10278-014-9717-9.

Teplan, M. 2002. "FUNDAMENTALS OF EEG MEASUREMENT M . Teplan." 2: 1–11.

Voytek, Bradley et al. 2010. "Shifts in Gamma Phase-Amplitude Coupling Frequency from Theta to Alpha over Posterior Cortex during Visual Tasks." *Frontiers in human neuroscience* 4(October): 191.

World Health Organisation, and Who. 2004. "World Report on Road Traffic Injury Prevention." *World*: 244. http://www.who.int/violence_injury_prevention/publications/road_traffic/world_report/en/.