Original Article

Integrated Biosignal Analysis to Provide Biomarkers for Recognizing Time Perception Difficulties

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Abstract

Background: Time perception refers to the capability to recognize the passage of time. The cerebellum is located at the back of the brain, underlying the occipital and temporal lobes. Dyschronometria is a cerebellar dysfunction, in which a person cannot precisely estimate the amount of time that has passed. Cardiac indicators such as heart rate (HR) variability have been associated with mental function in healthy individuals. Moreover, time perception has been previously studied concerning cardiac signs. Human time perception is influenced by various factors such as attention and drowsiness. An electroencephalogram (EEG) is a suitable modality for evaluating cortical reactions due to its affordability and usefulness. Because EEG has a high sequential outcome, it offers valuable data to explore variability in psychological situations. An electrocardiogram (ECG) records electrical signals from the heart to examine various heart conditions. The electromyography (EMG) technique detects electrical impulses produced by muscles. **Methods:** EEG, ECG, and EMG are integrated during time perception. This study evaluated the human body's time perception through the neurological, cardiovascular, and muscular systems using a simple neurofeedback exercise after time perception tasks. The three biosignals which are EEG, ECG, and EMG were investigated to use them as biomarkers for recognizing time perception difficulty as the main goal of the study. Five healthy college students with no health issues participated, and their EEG, ECG, and EMG were recorded while relaxing and performing a time wall estimation task and neurofeedback training. Previous research has shown the relationship between EEG frequency bands and the frontal center during time perception. Investigating the connection between ECG, EEG, and EMG under time perception conditions is significant. **Results:** The results show that ECG (HR), EEG (Delta wave), and EMG (root mean square) are critical features in time perception difficulties. **Conclusion:** The ability and outcomes of multiple biomarkers might allow for improved diagnosis and monitoring of the progress of any treatment applications such as biofeedback training. Furthermore, those biomarkers could be used as useful for evaluating and treating dyschronometria.

Keywords: *Electrocardiogram, electroencephalogram, electromyography, time perception*

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Introduction

The brain is a complicated system of connected fibers that transmit electrical signals.[1] It comprises three areas: the cerebrum, cerebellum, and brainstem.[2] The cerebrum, which is the central portion of the brain, consists of the right and left cerebral hemispheres. Senses such as touch, vision, hearing, speech, emotions, learning, and self-control of movement are cerebellar functions.[2] The brainstem is linked to the cerebrum, cerebellum, and spinal cord.[2] The synchronous electrical movement inside a neuronal network can be detected using an electroencephalogram (EEG).[3] Cardiac waves have been linked to a wide variety of mental statuses.[4] EEG electrical signals are divided into numerous frequency waves by filtering the EEG electrical signals as delta, theta, alpha, beta, and gamma, and each frequency has different ranges.[5] Cardiac waves reflect the role of the autonomic nervous system (ANS) and its immediate influence on cardiac activity.[6] For example, increasing the heart rate (HR) through exercise does not considerably affect time perception.[7] However, other cardiac signs offer a more comprehensive indication of the ANS such as HR variability (HRV) which is reflected as a warning of future health problems.[7]

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The heart is innervated by the sympathetic nervous system (SNS) and parasympathetic nervous system (PNS).[8] Thus, various HRV components can be attributed to the SNS and PNS.[8] The frequency and time domains of HRV reveal the heart condition.[9] Over the past decade, researchers have used EEG,[10] electrocardiogram (ECG),[4] or electromyography (EMG)[11] to describe and evaluate their influence on time perception. Previous studies observed connections between time perception and HR.[12] For example, one study found that individuals have improved fundamental precision at replicating periods when their HR decelerates throughout the sample interval encoding.[13] As the PNS is responsible for reducing HR and is also the principal factor determining HRV, individuals with higher PNS activity perform better.[14] The biological alteration in the HR, monitored by the ANS, is identified as HRV. HRV is extracted from ECG with the help of the QRS complex.[15,37]

Time-domain indicators of HRV are used to assess the quantity of irregularity around the magnitudes of the interbeat interval, which is the period between continuous heartbeats.[9]

Frequency-domain indicators assess the allocation of complete or comparative power to four frequency bands.[9] The association between the ANS function, temporal reproduction, and muscular system requires additional investigation[16,17] The central nervous system and ANS immediately influence how humans observe time.[18,38]

Precise time assessment is vital for perception.[19] Previous neuroimaging experiments on humans implied that perceptual timing involves several brain zones.[20] The results show that duration information appears in numerous brain lobes, including the bilateral parietal cortex, right inferior frontal gyrus, and medial frontal cortex.[20]

However, individual differences in the duration judgment are associated with the accuracy of interpretation of the duration in the right parietal cortex.[20] Neurophysiology uses EEG to identify brain disorders such as epilepsy.[21,36,42]

One of the extensively applied procedures for analyzing EEG data is to decompose the electrical signal into frequency bands.[22,39,41] This implies a breakdown of the EEG signal into frequency elements through a fast Fourier transform (FFT).[22] In spectral analysis, it is common to take the square of the absolute magnitudes of FFT to estimate the power spectral density (PSD).[22] The frequency bands are delta (0.5–4 Hz), theta (4–7 Hz), alpha (8–12 Hz), beta (12–30 Hz), and gamma (30–100 Hz).[9,40]

The 10–20 system is the traditional electrode placement method that is used to gather EEG data.[23] According to this system, each electrode location is characterized by a sign to categorize the lobe or part of the brain the electrode is reading.[23] In addition, even numbers point to the right side of the brain, whereas odd numbers point to the left side.

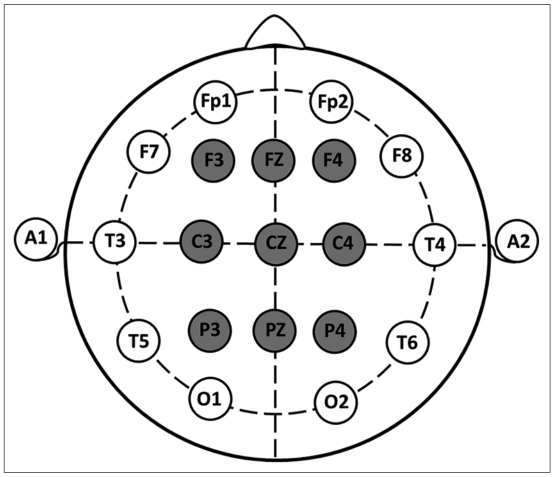

Figure 1: The 10–20 electrode positions

EMG signals are biomedical signals that determine the electrical flows produced in muscles during contraction, indicating neuromuscular events.[24] The nervous system constantly controls muscle action. Consequently, the EMG signal is a problematic signal manipulated by the nervous system and differs based on the body and physiological states of the muscles.[25]

Previous research has evaluated the correlation between ECG and time perception. They found that individuals with advanced HRs and low-frequency (LF) modules of HRV were linked with a less precise perception of time, indicating that time perception could be modulated by ANS events.[4] The ECG features included HR, root means square of successive relative risk interval differences (RMSSD), high frequency (HF), and LF.[4]

Furthermore, an EMG study claimed that the phenomenon of electromyographic gradients increases muscle activity during cognitive tasks that involve prolonged attention, which is a critical function in perceptual timing.[11] They evaluated the facial muscle dynamic activity indices over time. They concluded that the electromyographic activity in the corrugator supercilii over time reflected objective time, and this association forecasted assessments of duration.[11]

In addition, the zygomaticus major muscle signaled a bias that knowledge presents in duration judgments. Rectification is the translation of a natural EMG signal to a signal with a specific polarity, typically a positive sign.[26] The objective of rectifying the signal is to confirm that the signal ensures a nonzero mean because the raw EMG signal has positive and negative components.[26]

However, in this study, the instrumentation included EEG, ECG, and EMG to evaluate time perception. The goal was to increase the number of measurements related to the human body to consider their correlation in depth.

The time wall estimation task[27] was used for subjects in three conditions: rest, performing a time perception task, and neurofeedback. This task is an essential time/movement estimation task in which a moving item disappears behind a wall, and the subject must judge when it would have touched a gap.

In this study, the EEG, ECG, and EMG features were extracted and evaluated. The study amplified the number of features to determine unexpected associations between the nervous, cardiovascular, and muscular systems.

Methods

This study evaluated EEG, ECG, and EMG features using MATLAB. The experiment involved three sessions (relaxation, time wall task, and neurofeedback) simultaneously. In the relaxation session, subjects were supposed to close their eyes, whereas in the task session, the time wall estimation was performed.[27] In the neurofeedback session, the subject was asked to take a deep breath every minute.

Subjects

Fifteen EEG, ECG, and EMG recordings were obtained from five right-handed male participants, who were graduate and undergraduate students with a mean age of 27.5 ± 3.1 years. An authorized consent form was obtained from all subjects.

Signal condition and feature extraction

Several filters were employed to eliminate physiological and nonphysiological artifacts from EEG, ECG, and EMG. For EEG, a band-pass filter of 1–35 Hz range was used, whereas EEG recordings using a Dry Sensor Interface-24 (DSI-24) and dry electrode EEG headset were performed.

DSI-24 is a wireless EEG headset that includes 21 electrodes at positions equivalent to the 10–20 international system, with a sampling rate of 300 Hz. ECG and EMG signals were recorded using a BioRadio device at a sampling rate of 960 Hz. EEG, ECG, and EMG recordings were simultaneously obtained. Electrodes F3, F4, C3, C4, P3, and P4 were selected for EEG signal analysis, and Fz, Cz, and Pz were the reference electrodes[Figure 1].

Statistical analysis

One-way ANOVA and Pearson's correlation were used to verify the significance and correlation between the EEG and ECG-derived features. All statistical analyses were performed using MATLAB R2017a.

Results

The biometric information of all the subjects is presented in Table 1. Participants were asked multiple questions about their lives. All subjects were right-handed and had a meal before the experiment. The responses are presented in Table 2.

Figures 2-4 show the rectified EMG signals for three different sessions, whereas Figures 5-7 show the PSD for the F3, F4, C3, C4, P3, and P4 electrodes.

Tables 3-7 show the estimation of five frequency bands: delta, theta, alpha, beta, and gamma, respectively, in three recording sessions: relaxation, time perception task, and neurofeedback.

Discussion

In this study, advanced instrumentation analysis was used to compare the performance of different biosignals. For the EEG analysis, the PSD was calculated for five frequency bands: delta, theta, alpha, beta, and gamma. In addition, ECG and EMG features were acquired. This study's significant benefit is that it assesses which instrumentation is better for evaluating the time perception disorder and indicates the best features for different research areas, such as mental status.

Table 1: Subjects information

Information	Data
Gender	Male: 5
Age	27.5±3.1
Weight	80±8.6
Height	170±2.2
BMI	28±0.7 kg/m^2

BMI – Body mass index

Table 2: Questions and answers about the subjects life

Questions	Answers
How often do you exercise?	1-2 days/week
Do you smoke?	Two yes and Three no
How many siblings do you have?	8.3±2.7
How many hours do you study (per day)?	3.5±1.0
Between 1 and 10, how important is time for you? (1 is the lowest)	8.3±0.4
Between 1 and 10, how often are you right on time for an appointment? (1 is the lowest)	7.5±0.57
When you have an appointment, how much earlier do you usually arrive? (Before)	6.25±1.1 min
Do you think you have a problem with timing?	Yes
How many hours per day do you sleep usually?	6.25±0.9 h

Table 3: Electroencephalogram features calculation delta

Feature*	Relax	Time task	Neurofeedback
F3	42±0.9	41±1.0	38±2.0
F4	42±0.4	41±0.7	40±0.6
C3	41±0.9	36±3.3	30±4.2
C4	40±1.2	38±1.4	34±4.0
P3	38±2.2	32±4.3	33±2.0
P4	41±0.5	35±2.0	26±6.0

$$*Feature = \frac{Summation\ of\ power\ from\ 0.5\ to\ 4\ Hz}{Total\ power} \times 100$$

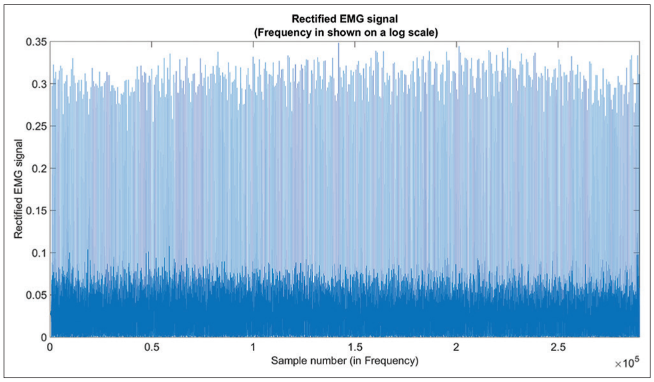

Figure 2: Rectified EMG signal: relax session. EMG – Electromyography

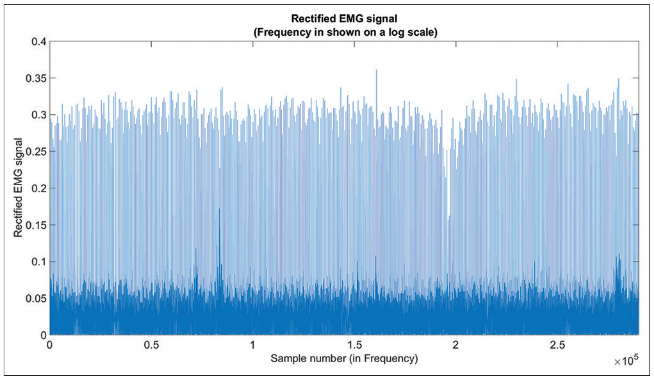

Figure 3: Rectified EMG signal: time task session. EMG – Electromyography

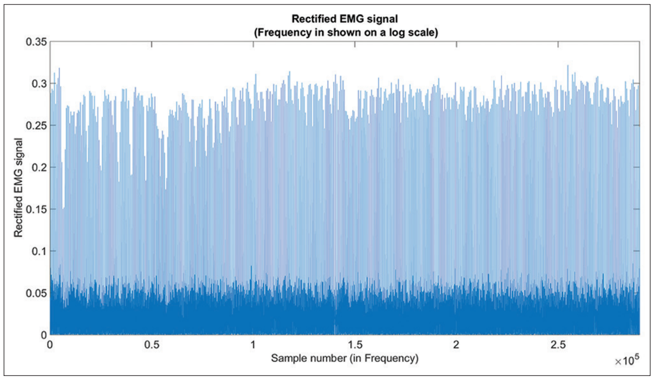

Figure 4: Rectified EMG signal: neurofeedback session. EMG – Electromyography

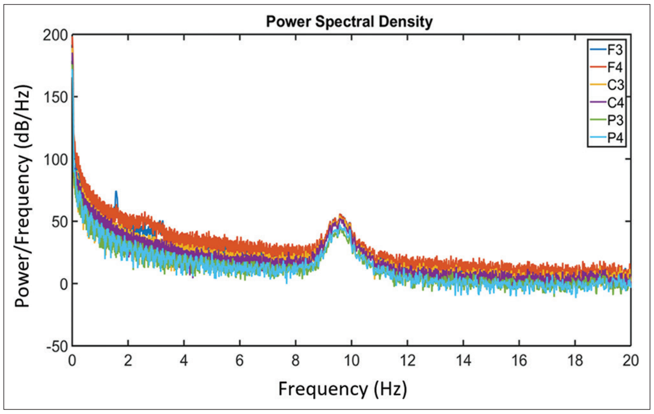

Figure 5: PSD for relax session: six electrodes. PSD – Power spectral density

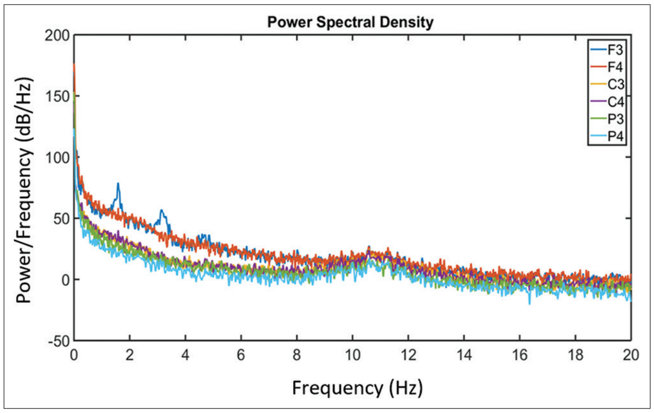

Figure 6: PSD for time task session: six electrodes. PSD – Power spectral density

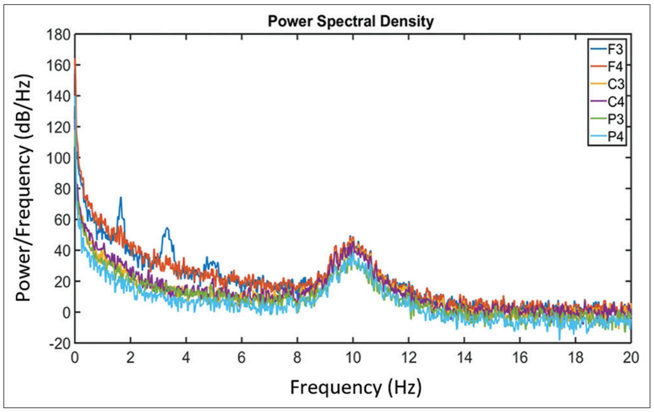

Figure 7: PSD for neurofeedback session: six electrodes. PSD – Power spectral density

Table 1 lists the body mass index (BMI) of subjects. An individual with a BMI of more than 28 is considered "overweight."[28] However, the average weight is recommended for better time perception.[29] Table 2 lists the different answers from the subjects; however, they all confirmed they had problems with time perception.

Figures 2-4 show the rectified EMG signals under the aforementioned three sessions. The amplitude of EMG signals decreased threefold, indicating muscle forces during the time perception task.[30]

The frequency bands are delta (δ: up to 4 Hz), theta (θ: 4–8 Hz), alpha (α: 8–15 Hz), beta (β: 15–32 Hz), and gamma (γ: ≥32 Hz) waves, as clearly shown in Figures 5-7.

From these figures, the alpha band appears in the relaxation session in the frequency range of 8–15 Hz, while it disappears in the time perception session. The alpha band then appears in the neurofeedback session. The other frequency bands exhibit variations. However, alpha and theta are involved in different waking tasks in many parts of the brain.[31]

Table 4: Electroencephalogram features calculation theta

Feature*	Relax	Time task	Neurofeedback
F3	30±1.9	27±0.5	26±0.8
F4	29±0.1	28±0.3	28±0.1
C3	41±0.9	36±3.3	30±4.2
C4	40±1.2	38±1.5	34±4.0
P3	38±2.2	32±4.3	33±2.0
P4	41±0.6	35±2.0	26±6.0

$$*Feature = \frac{Summation\ of\ power\ from\ 4\ to\ 7\ Hz}{Total\ power} \times 100$$

Table 5: Electroencephalogram features calculation alpha

Feature*	Relax	Time task	Neurofeedback
F3	7.4±0.2	11±0.9	7.8±0.7
F4	7.5±0.3	11±0.8	8.0±0.4
C3	41±0.9	36±3.3	30±4.2
C4	40±1.2	38±1.4	34±4.0
P3	38±2.2	32±4.3	33±2.0
P4	41±0.5	35±2.0	26±6.0

$$*Feature = \frac{Summation\ of\ power\ from\ 8\ to\ 12\ Hz}{Total\ power} \times 100$$

Table 6: Electroencephalogram features calculation beta

Feature*	Relax	Time task	Neurofeedback
F3	0.6±0.3	2.3±0.5	2.3±1.1
F4	0.3±0.1	1.9±0.3	1.4±0.3
C3	41±0.9	36±3.3	30±4.2
C4	40±1.2	38±1.5	34±4.0
P3	38±2.2	32±4.3	33±2.0
P4	41±0.6	36±2.0	27±6.0

$$*Feature = \frac{Summation\ of\ power\ from\ 12\ to\ 30\ Hz}{Total\ power} \times 100$$

Table 7: Electroencephalogram features calculation gamma

Feature*	Relax	Time task	Neurofeedback
F3	0.5±0.3	0.7±0.4	1.6±0.9
F4	0.1±0.0	0.2±0.1	0.5±0.2
C3	41±0.9	36±3.3	30±4.2
C4	40±1.2	38±1.5	34±4.0
P3	38±2.2	32±4.3	33±2.0
P4	41±0.6	36±2.0	27±6.0

$$*Feature = \frac{Summation\ of\ power\ from\ 30\ to\ 100\ Hz}{Total\ power} \times 100$$

Tables 3-7 justify the estimation of these five frequency bands. As shown in Tables 3 and 4 for the delta and theta bands, the normalized power of all electrodes decreased in the time task and then fell in the neurofeedback session, except for electrode P3, which then increased gradually.[32]

As shown in Tables 5-7 for the alpha, beta, and gamma bands, the amplitudes of frontal electrodes (F3, F4) increased for the time wall task followed by a decrease in the neurofeedback session. The amplitudes of electrodes C3, C4, and P4 decreased in the time wall task and neurofeedback sessions. The amplitude of electrode P3 declined in the time wall task and then increased, similar to the delta and theta bands. These results are similar to those reported in previous articles.[33]

The ECG feature calculations in Table 8 demonstrate that the HR increased in the time wall task and neurofeedback sessions,[4] whereas RMSSD and HF decreased and then increased. In addition, those features are usually correlated.[34] In addition, LF and LF/HF increased and then decreased, indicating the impact of the two sessions.[34]

The EMG root mean square decreased in the time wall task and neurofeedback sessions. The average rectified value decrease showed a similar result for the neurofeedback session as shown in Table 9.[35]

A previous study investigated the correlation between ECG and time perception.[4] They found that individuals with elevated HRs throughout task performance tended to have reduced precision in the perception of time, supporting the previous investigation that linked sympathetic responses with a decline in impulsivity.[7] In this study, the EEG, ECG, and EMG features were examined in detail. The EEG electrode P3 shown in the figures and table is a better indicator of time perception. In addition, the ECG and EMG features showed an impact during the session. The neurofeedback was of low significance. The main limitations of this study were the number of subjects and noise from different sources.

ANOVA analysis showed that there were significant differences ($P > 0.05$) among some ECG, EEG, and EMG features. The statistical analysis showed significant results at $P < 0.05$ between ECG features as follows: HR versus RMSSD, HR versus HF, HR versus LF/HF, HR versus RMS, and HR versus HRV. In addition, the results showed significant differences between ECG and EEG features at $P < 0.05$, as follows: HR versus delta F3, HR versus delta F4, HR versus delta C3, HR versus delta C4, HR versus delta P3, and HR versus delta P4. Moreover, ANOVA analysis showed that there were no significant differences ($P > 0.05$) among any of the other ECG, EEG, and EMG features. Furthermore, there was not any statistically significant difference for any of the features among the three conditions time perception task, rest, and neurofeedback.

Conclusion

Biosignals play a direct role in recognizing cognitive status. The outcomes of this study will allow us to discover and understand the activity of the brain, heart, and muscles in many situations. Another contribution

Table 8: Electroencephalogram features calculation

Feature	Relax	Time task	Neurofeedback
HR	84±5.8	85±5.7	89±5.7
RMSSD	27±6.6	26±5.0	73±17
HF	35±8.0	19±3.4	37±7.0
LF	64±8.0	80±3.5	62±7.0
LF/HF	2.6±0.8	4.7±0.8	2.2±0.6

HR – Heart rate; RMSSD – Root means square of successive RR interval difference; HF – High frequency; LF – Low frequency

Table 9: Electroencephalogram features calculation

Feature	Relax	Time task	Neurofeedback
RMS*	0.18±0.05	0.16±0.06	0.15±0.06
ARV*	0.03±0.000	0.02±0.000	0.02±0.0005

*RMS signifies the square root of the average power of the EMG signal for a given period, #ARV determines the mean of the rectified or absolute value of the EMG signal amplitude. RMS – Root means square; ARV – Average rectified value; EMG – Electroencephalogram

of this study is that it can be useful in evaluating time perception disorders such as dyschronometria. Future research may be capable of precisely explaining how signals from the brain and heart influence our perception of time.

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Conflicts of interest

There are no conflicts of interest.

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