The Thirty-Third International
FLAIRS Conference (FLAIRS-33)

Music Stimuli for EEG-Based User Authentication

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Abstract

A brain signal based biometric system is a novel approach for more intuitive, robust, and user-friendly authentication. Although previous research has been conducted in this field with different visual stimuli, music stimuli for brain signal authentication is rarely considered. In this paper, a new framework for user authentication system with electroencephalography and music stimuli is proposed. The EEG data was routinely collected from 16 healthy participants once a week for three weeks. Though different types of music evoke different responses, users are able to be recognized based on their brain signals. The experiment results show that when using this approach, the best classification accuracy rate is around 96.75%. These results show that the musically evoked response carries participant discriminating features, which can be potentially employed as a biometric trait.

1 Introduction

The rapid development of wearable devices and sensor technology has promoted the further exploration of human biosignals in various domains. One of the frontiers in both science and technology research of bio-signals is brain activity, which can be measured by using *electroencephalography* (EEG), *magnetic resonance imaging*, or *electromyography*. The *electroencephalography* is a method for quickly determining how brain activity can change in response to stimuli. It was found to be useful in many applications like abnormal brain activity diagnosis, brain-computer interaction, affective computing, robotics adaptive learning, direct brain-to-brain communication (Jiang et al. 2019), and so on. In addition to the conventional fields, EEG signals have also been suggested for use in biometric authentication purposes.

Biometrics have various methodologies available for the study of metrics related to human characteristics. Electroencephalography signals are considered by many to be one of the most efficient and universal methods for examining these biometric measures. While commonly available methods of conventional biometrics make use of physiological or behavioral features, based on the individual's characteristics or the way they behave, EEG signal biometric systems rely on the use of cognitive and emotional brain states as their distinctive features (Li, Cha, and Tappert 2019). Previous research in both early neurophysiological studies and biometric studies have already pointed out that EEG signals provide relevant information about individual differences. Another reason for perceiving EEG as a promising technique to generate biometric templates is also because the activity of the brain signals is a more intuitive, robust, and user-friendly authentication modality. Additionally, EEG signals are very resilient against fraud and non-knowledgeable acquisition compared to other traditional biometrics such as fingerprint and facial recognition. . Due to the highly unique nature of brain signals, it is hard to steal or mimic (Thomas and Vinod 2017), and has the added benefit of allowing for continuous recognition (Li et al. 2019). However, the disadvantage of using an EEG signal authentication system is the challenge of setting up a user for data acquisition and creating an ideal stimulation environment.

Research for EEG extraction protocols for user recognition has been implemented from the baseline study with eyes-open (EO) and eyes-closed (EC) (La Rocca et al. 2014; Thomas and Vinod 2016) to different imagery stimulations (Rahman and Gavrilova 2016; Di et al. 2018; Li et al. 2019). The latest study has shown that the in-ear EEG technology and Auditory Evoked Potentials (Nakamura, Goverdovsky, and Mandic 2017; Kidmose, Looney, and Mandic 2012) is a potential solution to narrow this gap. Inspired by these studies, this research attempts using music stimuli to evoke brain signals for user authentication and a new approach in the field of EEG-based biometrics is proposed as shown in Figure 1. In addition to the authentication approach, this study continued to track the distinctiveness of the EEG signals of 16 subjects over three weeks. A single channel and pairwise channel modality of the EEG system is also evaluated and the relevant results were mapped. In order to adapt to practical applications, the study adopted traditional statistical parameters and dynamic histogram models with dichotomy transformation for feature extraction and applied the suggested classifier in (Li et al. 2017; Siuly, Li, and Zhang 2018) to examine the dataset.

The rest of the paper is organized as follows: Section 2 outlines the related works of EEG-based studies. Section 3

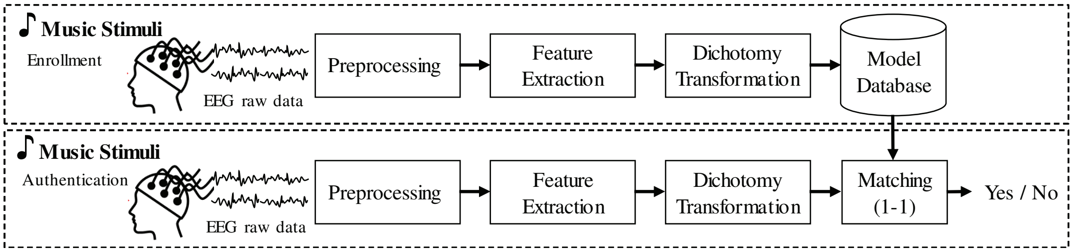

Figure 1: Proposed biometric authentication system

describes the experimental protocol, the music stimulus presentation, data collection materials, as well as the data preparation process. Section 4 discusses the experimental results, and in the Section 5 is the conclusion and future work.

2 Related Works

Research into EEG-based user authentication has done much to lay the foundation of this study. As cognitive biometrics, EEG signals offer a high degree of uniqueness among individuals and contain a great deal of information about that individual. Additionally, it also provides significant benefits over other user-recognition schemes. When compared to other accepted biometrics such as voice, fingerprint, and face recognition, brain signals have a much higher degree of "universality" (Chan et al. 2018). For example, people with speech or language impairments may struggle to use voice recognition software and individuals with missing or damaged fingertips cannot use fingerprint recognition software; but a brain that produces an electrical signal can be used with an EEG for biometric recognition.

Aside from that, not all biometric techniques offer the same level of security. For instance, fingerprints can be left behind on surfaces or damaged in accidents. Faces can also be photographed with a camera or covered by a mask. From a security perspective, that biometric information is 'public'. They can be captured without the owner's knowledge and replicated to bypass whatever security measures are in place. In the case of large scale data breaches, like the 2015 hacking of the United States Office of Personnel Management, the personal information and 5.6 million fingerprints of federal employees were stolen (Gootman 2016), rendering them useless for future authentication. Although brain signals have limitations, they are not exposed or left behind like other popular biometric features. Measuring these signals requires physical contact with the head. Therefore, it is difficult to obtain this data without the user's participation, and the nonstationary characteristic of EEG signals paired with each person's unique neural pathways and response to stimuli makes it impossible to imitate (Bashar, Chiaki, and Yoshida 2016). All of these qualities make this type of biosignal an attractive choice for biometric security (Thomas and Vinod 2017).

Despite recent interest in this area of research, stimulus tends to fall mainly into merely three categories: Rest, Text, and Images/Video (Table 1 summarizes the related work concerning user authentication via brain signal analysis). Resting state stimulus with eyes-closed and eyes-open is a baseline in the study of EEG for biometrics. In 2016, researchers using the public database PhysioNet BCI were able to classify resting state EEG signals of 109 subjects with an average accuracy of 99.7% for beta-band in frequency (15-30Hz) (Thomas and Vinod 2016). Although that classification result reached a relatively high accuracy rate, which demonstrates the potential of the use of EEG, the resting stage EEG signals is not enough to be applied for real-world applications. Since in real cases, people do not only stay resting when interacting with computers.

EEG experimentation done by Rahman et al. explored the use of text stimulus to find the best signal band for user verification. They considered the alpha, beta, and theta bands both independently and in combination with each other. Their results with a *back propagation neural network* (BPNN) highlighted the benefits of analyzing each signal band in isolation. The alpha, beta, and theta bands had a classification rate of 84.4%, 80%, and 78.1% respectively; while the alpha-theta (65.6%), alpha-beta (64.1%), beta-theta (58.8%), and alpha-beta-theta (56.9%) combination bands had much lower accuracy overall (Rahman and Gavrilova 2016). Di et al. of Tianjin University used a *convolutional neural network* (CNN) for their user identification research using text stimulus. The EEG signals were measured by extracting the P300 wave as the event-related potential components elicited in the process of decision making, and they were able to reach around 99% accuracy when classifying 33 subjects (Di et al. 2018) in multi-class classification.

In a video stimulus study, researchers set out to document potential differences in classification rates when analyzing signals from subjects who viewed both Virtual Reality (VR) and Non-VR videos. Their findings showed a small but significant difference of approximately 3% when classifying VR (73.68%) vs Non-VR (76.73%) data when using their best feature extraction method, a hybrid autoregressive (AR) and statistical model, and *support vector machine* (SVM) classifier with non-linear kernel (Li et al. 2019). Koike-Akino et al. completed a study that made use of Zener Cards (Kennedy 1938) as a form of digital image stimulus. 25 volunteers were tasked with selecting one of five cards on the screen and counting the number of times their card appeared. This data set in conjunction with *principal component analysis* (PCA) as feature extraction and *quadratic*

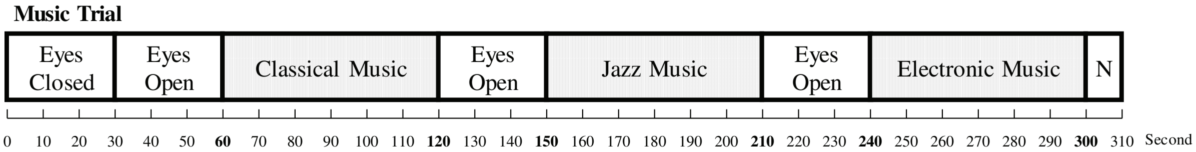

Figure 2: Music trial test procedure

discriminant analysis (QDA) as classifier reached 96.7% accuracy (Koike-Akino et al. 2016). A smaller study of only four subjects attempted to "investigate the efficacy of self-related visual stimuli" (Thomas, Vinod, and others 2017) by showing subjects pictures of different faces. With a classifier based on Pearson's Correlation Coefficient (PCC) they were able to finish this study with an average accuracy of 87.5%. Straticiuc et al., who performed "a preliminary analysis of music on human brainwaves" found that music resulted in an increase in alpha waves and a dramatic decrease in beta waves (Straticiuc et al. 2016). However, no attempt at classifying subjects was made. The use of musical stimulus for biometric analysis remains a somewhat unexplored area of study. Hence, this study attempts to fill that gap with different types of music stimuli.

3 Methodology

To explore music stimulation for the EEG-based user authentication system, this research developed a specific music trial program along with carefully designed EEG data acquisition steps. This section will elaborate on the data acquisition process, signal processing, and feature extraction methods used in this study.

Data Acquisition

In this research, EEG data was collected from 16 healthy participants (7 female, 9 male), with an average age of 26 years old ± 3 years. Before each session, the volunteers received an average of 7 hours of sleep. The participants are required to return for multiple sessions of data acquisition, with each having EEG data collected once a week for three weeks. Each week, the volunteers participated in a 5-minute test session of music stimuli. The time frames of the test session are illustrated in Figure 2. The first 60 seconds is designed for the baseline study with 30 seconds eyes-closed (EC) and 30 second eyes-open (EO) rest. After the 60 seconds of rest, participants would then listen to three songs broken by 30 second periods of EO rest. The songs consisted of three different genres of music: classical, jazz, and electronic. The same songs were played in the same order during each session.

EEG recording and channel location

The data was recorded using an OpenBCI Utracortex "Mark IV" EEG headset with Cyton board. The default data amplifier is 250Hz sampling frequency and the EEG signals were recorded from 8 channels (T3, T4, C3, C4, Cp5, Cp6, Oz, and Fz), with 2 references (A1, and A2). As shown in Figure 3, the EEG electrodes were placed in accordance with the international 10-20 system. The 8-channels were selected to target the left and right auditory cortices, one for the frontal area, and one for the Occipital area.

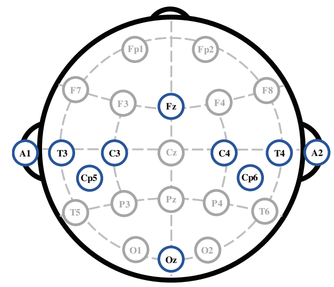

Figure 3: Chosen Electrode Locations

Pre-processing

Before feature extraction, the raw EEG signals are pre-processed according to the conventional signal processing procedure. First, 'bad channels' are removed; a channel is considered 'bad' if it is not working or otherwise has trouble making comfortable contact with the subject during the data collection process. A notch filter of 60Hz is then applied to remove background noise from power lines. After that, data is downsampled from 200Hz to 128Hz to reduce the data size. The EEG signals contain five major frequency bands: delta (0-4Hz), theta (4-8 Hz), alpha (8-15 Hz), beta (15-30 Hz), and gamma ($>$30Hz) bands. In this study, only the frequency range from 4-45Hz is considered because the delta-band dominates in deep sleep states and the high gamma-band is correlated with selective attention. The data passes through the band-pass filter and the relevant data is separated. After pre-processing, data is prepared for feature extraction. In this step, data from the musical stimuli are isolated and rest data is discarded.

Feature Extraction

The methods for extracting the characteristics of the EEG signal after pre-processing are diverse. There are three types of features that can be obtained from the EEG data: time-domain, frequency-domain, or time-frequency domain. This study considered time-domain features and time-frequency domain features. First, a conventional statistical feature extraction method which was also examined in the research (Li and Cha 2019) is used. The statistical parameters used are mean (μ), median (m), standard deviation (σ), z-score (z),

Table 1: Related work concerning user authentication via brain signal analysis.

Author	Subjects	Stimulus	Features	Classifier	Accuracy %
(Thomas and Vinod 2016)	109	Rest	Sample Entropy, PSD	Mahalanobis Dis.	99.7
(Rahman and Gavrilova 2016)	10	Text	Entropy, Statistics	KNN	40-50
				BPNN	56.9-84.4
(Di et al. 2018)	33	Text	n/a	CNN	99
(Li et al. 2019)	29	Video	AR, PSD, Statistics	SVM	70.92-76.73
(Koike-Akino et al. 2016)	25	Images	PCA	QDA	96.7
(Thomas, Vinod, and others 2017)	4	Images	PSD	PCC	87.5

skewness (q), and kurtosis (k), which are given in equations (1) - (6).

$$\mu = \frac{1}{n}\sum_{i=1}^{n} X_i \tag{1}$$

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - \mu)^2} \tag{2}$$

$$m = \frac{1}{2}(X_{\lfloor \frac{n+1}{2} \rfloor} + X_{\lceil \frac{n+1}{2} \rceil}) \tag{3}$$

$$z = \frac{x_i - \mu}{\sigma} \tag{4}$$

$$q = \frac{1}{n}\sum_{i=1}^{n}(\frac{X_i - \mu}{\sigma})^3 \tag{5}$$

$$k = \frac{1}{n}\sum_{i=1}^{n}(\frac{X_i - \mu}{\sigma})^4 \tag{6}$$

In addition, to adopt the frequency components as the features to represent the EEG signals under music stimulation, a dynamic histogram measurement model with segmentation (DHMS) (Li 2019) is used. The dynamic histogram measurement model with segmentation is a novel approach to high-quality feature extraction by estimating the energy distribution of the EEG signals based on the time-frequency domain. In this research, the EEG data is segmented based on 10 second frames with 75% overlapping. The DHMS is described in Algorithm 1. The differential coefficient f is given as

$$f(x) = \frac{d_x}{d_t} = \frac{|x_n - x_{n-i}|}{\Delta_t}, \qquad \text{for} \quad i = [1, 2] \tag{7}$$

where, x_n is the data sample of a sequence, t represent the time points of the data sample x, and i is the step of the differential coefficient.

Classification

EEG user authentication is the task of determining whether two samples, X and Y, were collected from the same person or from two different people. Before passing the features into the classification machine, a feature domain transformation is applied on the extracted features. Classifying the distinctiveness of 16 individuals is a multi-class classification problem. However, with the use of the Dichotomy Transformation Model (Srihari et al. 2002), it can be turned

Algorithm 1: DHMS model for feature extraction

Input : A data sequences S, k is the number of segments with number of overlapping p
Output: A feature set F

Segment the data sequence S with p overlapping;
$X_n^k \leftarrow$ the kth sub-sequence of S ;
for $i \leftarrow n$ **to** 1 **do**
  $f_a \leftarrow$ differential coefficient of x_n and x_{n-1};
  $f_b \leftarrow$ differential coefficient of x_n and x_{n-2};
end
$H_x^k \leftarrow$ histogram frequency of sub-sequence x_n;
$H_a^k \leftarrow$ histogram frequency of sub-sequence f_a;
$H_b^k \leftarrow$ histogram frequency of sub-sequence f_b;
$F \leftarrow \{H_x^k, H_a^k, H_b^k\}$

into a binary-class classification problem to meet the purpose of user authentication. Each pair of features from the feature extraction phase were computed with Euclidean distance thereby transforming from polychotomy to dichotomy. Feature pairs from the same person (intra-class) are labeled '0', and feature pairs from separate persons (inter-class) are labeled '1'. They are then trained for the model in a *support vector machine* (SVM) algorithm with a linear kernel. The experiment details and classification results will be described in the next section.

4 Experiments and Results

This section describes the details of the proposed system with three categories of music stimulation in the EEG-based authentication systems, as well as the recognition performance on single-channel modality and pairwise-channel modality of the EEG system. All the results reported here are used in the form of an accuracy percentage with the mean value for the channel modalities as well as false acceptance rate (FAR) to represent the percentage of 'false positives' allowed in by the models.

During the experiments, the EEG data was synced and matched with the music trails. Data was segmented based on the time series of music track; the data range for M1 = [60:120], M2 = [150:210], and M3 = [240:300]. Each series was then evaluated for performance of both individual channels and also the bipolar channels (same location on

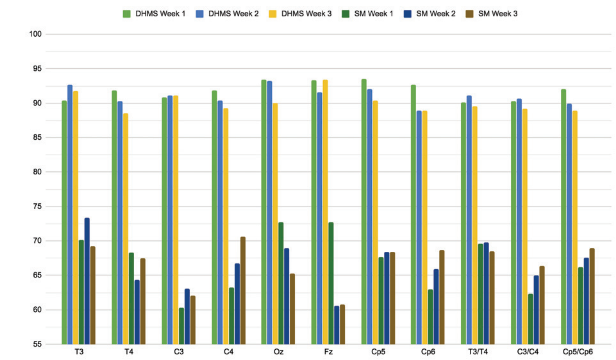

Figure 4: The average accuracy for single-channel and pairwise-channels modalities in week1, week2 and week3.

the left and right hemisphere) for synchronization purposes. Figure 4 shows the overall average accuracy for single-channel and pairwise-channels modalities in week 1, week 2 and week 3. Table 2 presents in detail both the recognition performance and the false acceptance rate for the single-channel and pairwise-channel modalities with music track 1 (M1), track 2 (M2), and track 3 (M3).

In terms of accuracy rate the DHMS outperformed the conventional statistical features in every channel. The average accuracy for all channels across all three weeks was 91.32% (single-channel) and 90.20% (pair-channel) for the DHMS model, and 66.75% (single-channel) and 67.15% (pair-channel) for the statistical model. As for false acceptance rate, the average FAR was 5.66% (single-channel) and 6.14% (pair-channel) for the DHMS model, and 33.29% (single-channel) and 32.58% (pair-channel) for the statistical model. Again averaging the channels, week 1 had the highest accuracy for both single (92.26%) and pair-channels (90.79%), followed by week 2 (91.27% single, 90.59% pair), and finally week 3 (90.43% single, 89.22% pair). Overall, the highest accuracies are not achieved in week 3, but instead in week 2. Also, comparing the modalities, we find that the C3 and Fz channel, and the C3/C4 and T3/T4 pairs show a near consistent result for all the weeks. It proves that collecting the EEG data near the auditory cortex can achieve a relatively stable accuracy in music stimuli for the authentication scheme.

5 Conclusions

This study proposes a new framework for EEG-based user authentication with music stimuli. A new EEG database consisting of 16 healthy subjects being stimulated by music once a week for three weeks was created for the purpose of testing this system and the viability of musical stimuli for user authentication. This model was capable of performing user authentication with an average accuracy across all weeks of 91.01%.These results show that the musically evoked response carries participant discriminating features, which can be potentially employed as a biometric. For future work, an expansion of the dataset beyond three weeks is already underway. Though an expanded study with a larger sample size and more ambitious time frame would also be beneficial. Analysis of authentication rates as users become more accustomed to the musical stimuli over an extended period of time could shed light on trends inherent to this type of stimulus or authentication model.

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Table 2: Accuracy and False Acceptance Rate for single-channel and pair-channel modalities with the DHMS and Statistical Features models

		Dynamic Histogram								Statistical Features							
		Accuracy (%)				False Acceptance Rate (%)				Accuracy (%)				False Acceptance Rate (%)			
Week	Channel	M1	M2	M3	Mean	M1	M2	M3	Mean	M1	M2	M3	Mean	M1	M2	M3	Mean
1	T3	90.14	91.47	89.48	90.36	5.26	5.11	7.56	5.98	70.40	68.78	71.21	70.13	29.39	30.98	26.53	28.97
	T4	89.40	94.87	91.40	91.89	7.86	3.71	5.93	5.83	67.38	68.61	68.85	68.28	33.37	34.28	25.59	31.08
	C3	89.55	91.69	91.25	90.83	7.41	5.56	5.71	6.23	65.26	56.85	58.91	60.34	34.33	46.47	45.06	41.95
	C4	90.40	92.58	92.65	91.88	4.74	5.04	4.97	4.92	62.97	63.25	63.41	63.21	41.55	41.05	37.79	40.13
	Oz	92.65	95.46	92.28	93.46	5.63	2.30	4.82	4.25	71.21	74.51	72.38	72.70	29.19	26.32	33.17	29.56
	Fz	96.75	90.35	93.01	93.37	3.72	6.85	5.28	5.28	77.15	70.14	70.79	72.69	26.09	37.28	36.62	33.33
	Cp5	93.54	93.76	93.39	93.56	3.71	3.34	3.85	3.63	69.96	65.70	67.41	67.69	26.72	38.79	34.21	33.24
	Cp6	91.10	94.17	92.84	92.70	6.75	2.82	4.52	4.69	64.96	59.37	64.46	62.93	37.40	41.71	35.19	38.10
	T3/T4	88.90	91.62	89.75	90.09	6.90	4.97	6.75	6.21	69.60	68.40	70.86	69.62	30.45	32.93	25.31	29.56
	C3/C4	88.18	91.67	90.97	90.27	7.20	5.64	5.82	6.22	64.97	61.68	60.22	62.29	37.81	45.22	40.99	41.34
	Cp5/Cp6	91.65	91.87	92.47	92.00	4.49	4.27	4.56	4.44	68.43	63.72	66.37	66.17	32.48	38.73	34.91	35.37
2	T3	93.35	93.80	90.99	92.71	4.52	4.74	5.63	4.97	72.75	73.89	73.59	73.41	23.02	22.62	26.35	24.00
	T4	91.43	89.51	89.96	90.30	4.89	6.52	7.04	6.15	65.52	66.81	60.58	64.31	36.16	31.88	42.93	36.99
	C3	92.98	90.21	90.25	91.15	4.08	6.30	6.00	5.46	60.75	64.73	63.62	63.03	38.86	33.83	36.59	36.42
	C4	89.77	89.44	91.91	90.37	5.49	6.08	5.93	5.83	66.16	67.59	66.63	66.79	34.37	28.57	31.95	31.63
	Oz	92.95	95.23	91.53	93.24	4.65	3.37	5.46	4.49	67.94	67.72	71.15	68.94	31.79	34.15	28.99	31.64
	Fz	93.58	90.62	90.43	91.54	3.77	5.86	5.22	4.95	61.54	59.55	60.59	60.56	40.70	41.33	38.41	40.14
	Cp5	91.95	92.91	91.14	92.00	6.00	5.04	5.49	5.51	67.71	69.82	67.79	68.44	29.66	26.59	31.05	29.10
	Cp6	89.81	89.14	87.67	88.87	6.00	7.26	10.82	8.03	67.86	66.74	63.19	65.93	30.11	34.66	37.67	34.15
	T3/T4	91.65	91.67	90.14	91.15	4.56	4.90	6.94	5.46	69.93	71.30	68.20	69.81	27.92	25.89	33.51	29.11
	C3/C4	91.21	90.14	90.71	90.69	4.67	5.38	5.93	5.33	64.01	66.02	65.08	65.03	36.52	30.40	33.75	33.56
	Cp5/Cp6	90.21	90.18	89.40	89.93	5.82	6.23	7.23	6.43	68.71	68.67	65.44	67.61	29.11	28.88	35.26	31.09
3	T3	93.17	87.56	94.46	91.73	3.93	9.49	2.52	5.31	70.14	68.08	69.56	69.26	26.72	31.27	29.03	29.01
	T4	90.21	85.16	90.40	88.59	6.89	8.90	6.23	7.34	67.32	67.99	67.05	67.46	30.31	32.20	35.55	32.69
	C3	89.59	90.25	93.57	91.14	6.30	5.78	3.56	5.21	60.96	62.31	62.75	62.01	39.06	38.88	38.43	38.79
	C4	92.10	85.86	89.81	89.25	3.93	10.08	7.78	7.26	71.17	69.82	70.93	70.64	24.87	26.72	28.21	26.60
	Oz	89.62	89.73	90.69	90.02	6.00	5.63	5.63	5.76	66.70	64.98	64.22	65.30	31.84	31.34	32.68	31.95
	Fz	93.45	91.77	94.95	93.39	4.52	5.84	3.86	4.74	63.68	58.96	59.67	60.77	35.42	40.22	38.99	38.21
	Cp5	91.84	87.33	91.95	90.37	6.67	8.23	5.11	6.67	68.46	68.50	68.12	68.36	31.32	31.34	30.73	31.13
	Cp6	92.32	85.78	88.66	88.92	5.78	9.56	7.04	7.46	70.55	69.25	66.38	68.72	27.12	30.42	32.73	30.09
	T3/T4	91.06	85.87	91.76	89.57	5.71	10.13	5.27	7.04	68.66	67.79	68.98	68.47	27.65	31.56	32.32	30.51
	C3/C4	90.14	87.05	90.51	89.23	5.38	8.35	6.34	6.69	66.58	65.54	66.99	66.37	32.21	32.62	32.59	32.47
	Cp5/Cp6	91.51	85.10	90.01	88.87	5.79	10.76	5.68	7.41	70.54	69.03	67.29	68.96	28.36	29.77	32.37	30.17

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