Finding EEG Correlates of ABO Blood Types

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Abstract

The goal of the present study is to investigate oscillatory features of electroencephalogram in individuals of different ABO blood types with the ultimate aim of identifying distinctive features between blood types in physiological signals. EEG signals have been recorded by four electrodes on scalp from 25 subjects at resting state with eyes open. The power spectral densities have been estimated and analyzed in each of the four frequency bands from 4 to 50 Hz. Statistical analysis and classification using the support vector machines have been carried out, and significant differences are found among subjects with different ABO blood types. Our results indicate that the frequency analysis of EEG data is significantly contingent upon ABO blood type.

Keywords: EEG, ABO blood type, Pattern Recognition, Brain-Computer Interface

1. Introduction

The ABO blood group is the most significant blood factor in clinical applications involving blood transfusions. With the recent ability to rapidly sequence genes, the ABO blood group is also recognized as a valuable asset for determining human migration patterns and ethnic origins. Despite the relative simplicity of the A and B antigens, perhaps especially considering the minor biochemical difference between them, the ABO blood group system remains one of the most interesting, both clinically and scientifically, dividing the world's population including patients and donors into four groups irrespective of origin or creed.

Since K. Landsteiner discovered the ABO blood group, many subsequent studies have investigated the relationship between blood groups and various features. Popular books have been supplemented by scientific studies on a possible connection between blood type and personality traits in normal populations [1-3]. Medical science has investigated the relationship between blood group and different diseases [4], while clinical studies have identified associations between blood type and psychological disorders [5-6].

Flegr *et al.* investigated for effects of RhD phenotype on toxoplasmosis- or agingassociated changes in the personality profile of about 302 blood donors, and found that Rhpositive and Rh-negative subjects responded differently to a parasitic disease. They also found effects of RhD phenotype on ego strength, protension, and praxernia. These results indicate that RhD phenotype might influence not only the effect of toxoplasmosis but also the effect of aging on specific personality traits [4]. Eysenck found that anxiety and neuroticism levels of a country appeared to vary consistently with the proportion of Type B blood group individuals. He also found that introversion varied with the proportion of Type AB blood group individuals [5]. Marutham and Indira initially found no difference between blood groups and extraversion, neuroticism and 'Type A behavior', but after dividing the groups on the basis of EPI norms, found that blood type Bs had higher scores on neuroticism than did any other group [6]. However, no previous articles have reported neuronal correlates of ABO blood types.

Nowadays, electroencephalogram (EEG) analysis has received considerable attention as the target of brain research. The EEG provides important insights into brain functions by revealing the location and sequence of neural activities, thereby pinpointing the origins of neurological disorders such as epilepsy [7], psychiatric illness sleep disturbances [8]. Furthermore, some previous studies have reported that the EEG shows differences by gender [9-10] age [11], emotion [12], and personal traits [13].

Güntekin and Başar reported that the amplitude of the occipital beta rhythm (15–24 Hz) is significantly larger for females than for males during the presentation of facial expressions depicting neutral, angry, and happy emotions [9]. Razumnikova also found gender-related differences in the alpha1 (8–10 Hz) and beta2 (20–30 Hz) patterns from 36 male and 27 female students while they solve a creative problem [10]. Gaál et al. documented that the absolute power spectrum of the EEG is higher in young subjects in the delta, alpha1, and alpha 2 frequency bands in the posterior area when both young and elderly participants are at rest with their eyes open [11]. Schmidt and Hanslmayr measured EEG alpha asymmetry to predict affective responses to musical stimuli, and results show that individuals with relatively higher alpha power over left frontal electrode sites [12]. Chi et al. investigated the relationships between EEG and personality dimensions such as positive affect, impulsiveness, empathy, and neuroticism [13]. Mikolajczak *et al.* showed that the pattern of resting EEG activation recorded in the frontal areas is significantly associated with emotional intelligence [14].

The authors have not found any report that would investigate the relationship between blood types and EEG so far. Thus, this study aims at finding distinguishable features from EEG data among ABO blood types. The goal of this research is to discover a correlation between the ABO blood type and EEG. The EEG signals of four scalp electrodes from participants at rest with eyes open were sampled to analyze their oscillatory features. Power spectral densities were derived from each of four frequency bands in the 4–50 Hz range. Classification using the support vector machine (SVM) was carried out to derive distinguishable features between blood types.

2. Methods

2.1. Subjects

The experiment was conducted on 25 healthy subjects (mean age, 21.57 ± 2.51 years; 12 women) were recruited from Sungkyul University (Anyang, Gyeonggi-do, Korea). Subjects comprised four blood type groups, including six A types (3 men and 3 women; mean age, 22.3 ± 3.0 years), three B types (2 men and 1 women; mean age, 22.0 ± 1.7 years), nine O types (4 men and 5 women; mean age, 20.7 ± 2.8 years), and seven AB types (4 men and 3 women; mean age, $22.0 \pm 2.0 \pm 2.0$ years). None of the subjects were currently taking drugs or medication, nor did any have a history of physical or mental illness. Before the experiment was conducted, all subjects were informed about the aim and scope of the study and gave written informed consent.

2.2. Procedure

Subjects were positioned approximately 100 cm away from an empty 24-inch LCD monitor and were asked to gaze at the black screen without any response while EEG recording was performed. A webcam was placed just above the monitor for recording eye blinks and body movements of the subjects during the experiments. The recorded video files were reviewed during the preprocessing of the EEG signal. The EEG signals were recorded using a QEEG-4, EEG recording system (Laxtha, Inc., Daejeon, Korea) with a sampling frequency of 256 Hz and band-pass filtered between 0.5 and 50 Hz. An additional 60-Hz notch filter was applied to avoid power line contamination. Ag/AgCl electrodes were placed on the F3, F4, C3, and C4 positions according to the International 10–20 system (Niedermeyer and Silva, 2003). The reference and ground electrodes were located at the bilateral mastoids.

2.3. EEG Data Analysis

EEG data analysis was performed by using MATLAB (Mathworks Inc., Natick, MA) and Telescan (Laxtha, Inc., Daejeon, Korea). A base line removal process was applied in order to eliminate some shift signals and to synchronize the zero levels of each channel. All signals were then band-pass filtered between 4.0 and 50.0 Hz in order to exclude unnecessary frequencies. The EEG data were then first segmented into non-overlapping epochs that were 2 seconds length (512 points). Epochs contaminated by ocular or body movements were manually excluded while reviewing the recorded video data. To reduce the computational complexity and deviation of individual differences due to their fundamental frequency rhythms, normalization was conducted using Eq. (1) so that the range became 0-1.

$$E_k = \frac{X_k - \min(X_k)}{\max(X_k) - \min(X_k)},\tag{1}$$

where E_k is the *k*-th normalized EEG data sample, and X_k is the *k*-th sample of the raw EEG data vector *X*. This preprocessing resulted in 100 EEG samples that consisted of 4 artifact-free epochs from each of 25 subjects.

A fast Fourier transform (FFT) in the frequency domain on the artifact-free EEG record was then performed. FFT converts a discrete time series X_n into frequency domain Y_k using the Eq. (2). Frequency bandwidths were divided according to the following divisions: theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–50 Hz).

$$Y_{k} = \sum_{n=0}^{N-1} X_{n} \exp\left(-i \cdot 2\pi \cdot N^{-1} \cdot nk\right), \qquad (2)$$

where k = 0, 1, ..., N-1.

From the computed FFTs, overall power spectral densities (PSD) were computed for each bandwidth by using Eq. (3)

$$PSD = \sum_{k=0}^{N-1} |Y_k|^2 = \frac{1}{N} \sum_{n=0}^{N-1} |X_n|^2 , \qquad (3)$$

The power spectral densities extracted from EEG signals of each blood type are evaluated using the SVMs. We use LIBSVM [15] which runs Sequential Minimal Optimization (SMO)

[16] that is widely used for quadratic programming problems. Eq. (4) is the objective function of SVMs.

$$f(x) = \sum_{i=1}^{M} \alpha_i^* K(X_i^*, X) + b^*, \qquad (4)$$

In this experiment, we analyzed four different frequency bands: theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and gamma (30-50 Hz). In addition, a separate analysis was performed for the betam band at 21-23 Hz. However, the power value of the delta band (0.1-4 Hz) was not evaluated since it is difficult to accurately separate artifacts due to eye movements from low activity of EEG signals [17-18].

Analysis of variance (ANOVA) were carried out using SPSS (SPSS Inc., Chicago, IL) to determine whether significant differences in EEG signals in subjects with different ABO blood types could be identified.

3. Results

The absolute power spectral density (Figure 1) showed that in the theta frequency band, EEG power in subjects with blood type B was lower than that in subjects in the other blood groups; in the alpha band, subjects with A and O blood types exhibited higher EEG power than that of B or AB type subjects. In the beta_m frequency band, A and B type subjects showed distinguishably higher EEG power than O and AB type subjects. However, no distinctive differences were observed in the gamma band.



Figure 1. Spectral power of frequency

The standard deviation between blood types of each frequency band is shown in Figure 2 in which previous findings are coherent to the results of standard deviation. In particular, standard deviation of $beta_m$ frequency is the highest one, logically compatible with the most distinctive patterns in Figure 1.



Figure 2. Standard deviation of the spectral powers

In order to find statistical correlations between blood type and the absolute spectral power for each frequency band separately, a 1-factorial analysis of variance (ANOVA) was performed with all samples of the absolute power spectra. As shown in Table 1, significant effects of blood type were observed in all channels of the alpha /beta frequency bands and in some channels in the theta/gamma bands. However, there was no significant effect in any channel of the beta_m band, unlike the finding in the power spectrum analysis.

According to these results, we chose the F3 and C3 channels of the gamma band, the F4 and C4 channels of the theta band, and all channels F3, F4, C3 and C4 of the alpha and beta band as the features to be used for distinguishing blood types.

Frequency	F3		F4		C3		C4	
	F	p-value	F	p-value	F	p-value	F	p-value
Theta	1.668	0.179	4.039	0.009	0.642	0.590	3.660	0.015
Alpha	4.441	0.006	5.257	0.002	5.110	0.003	3.848	0.012
Beta	4.596	0.005	5.110	0.003	3.335	0.023	3.792	0.013
Gamma	5.114	0.003	1.921	0.131	5.026	0.003	0.209	0.890
Beta _m	1.414	0.233	1.582	0.199	1.582	0.199	1.023	0.386

Table 1. Statistical comparison of the blood types in different frequency bands^a

^a Only comparisons significant after Bonferroni-correction (p-value.<0.05) are indicated in bold.

	1			1	
Pair	Frequency	Mean difference	Stdandard error	p-value	
A-B	beta	-0.006282	0.002181	0.029934	
A-0	alpha, gamma	0.004248	0.002715	0.023036	
A-AB	alpha, gamma, theta	0.009475	0.003343	0.005881	
B-O	-	-	-	-	
B-AB	beta	0.006963	0.002122	0.008657	
O-AB	beta, theta	0.005008	0.001613	0.017316	

Table 2. Significant differences of blood-type pairs

To figure out a blood type which makes dominant influence with statistical significance in Table 1, we have carried out post hoc analysis with Bonferroni correction. As a result, Table 2 shows that there are meaningful differences between A and B types in the beta frequency band of channels F3 and C3, between A and O types in the alpha band of F4 and C3, between A and O types in the gamma band of F3 and C3, between A and AB types in the alpha band of all channels, between A and AB types in the gamma band of F3 and C3, between A and AB types in the theta band of F4 and C4, between B and AB types in the beta band of F3 and F4, between O and AB types in the beta band of F4 and C4.

However, there is no significant difference between B and O types in any band or channel. The mean differences of each pair show statistical significances in Table 2.

To efficiently visualize the results of Table 2, we display Figure 3 indicating the exact positions on the scalp of the electrodes for the channels. For instance, the pairs that show significant distinctions on F3 are A-AB, A-O, A-B, B-AB. The purpose of the proposed study is to find characteristic features of EEG activation in individuals of different ABO blood types with the ultimate aim of identifying distinctions between blood types in EEG signals. To verify the proposed issues, SVM classification method was employed in order to demonstrate the results of the statistical analysis. We performed training and classification separately for each of the blood type pairs that were presented in Figure 3. The training stage identified an optimal separating hyperplane that divides the set of test examples into two classes. During the classification stage, each input point was assigned a label according to the side on which the point appeared with respect to the hyperplane. As we had only a small number of samples available for each blood type (A: 24, B: 12, O: 36, and AB: 28), 10-fold cross-validation was used to test the classification effectively.

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Figure 3. Channels that the significant differences of blood-type pairs found indicating the exact positions on the scalp of the electrodes for the channels



Figure 4. Recognition rates for blood-types shows, classification accuracy varied among the blood types, ranging from 68.33 to 80.77%

As Figure 4 shows, classification accuracy varied among the blood types, ranging from 68.33 to 80.77%. A and B types can be classified with 72.22% of recognition rate in beta of F3/C3, and A and O types can be classified with 68.33% of recognition rate in alpha of F4/C3, 69.23% in gamma of F3/C3. As for AB type, it can be classified with 69.23% of recognition rate in alpha of F3/F4, 80.77% in alpha of C3/C4, 75% in gamma of F3/C3 into A type, and with 68.75% in beta of F3/F4 into B type.

4. Discussions

Our results of the power spectral density and the standard deviation of each frequency band of EEG data shows there are distinguishable features in EEG signals among ABO blood types. However, blood has been known that it cannot effect to the brain due to the separation of circulating blood from the brain extracellular fluid in the central nervous system that is so called the blood-brain barrier [19]. Regarding this incompatibility, we review some studies that reported the relationship between blood and the brain. These studies may support our results that different neuronal signals were observed by different blood types. Studies of brain chemistry have documented a link between ABO group and certain differences in brain function. The effect of blood types on serotonin secretion in the brain was reported by Duncan and Rosse [20]. Their results demonstrated that serotonin release is blocked by antibody to platelet PIA1 antigen. An enzyme called monoamine oxidase (MAO) is responsible for the breakdown or inactivation of adrenaline and noradrenaline. When measuring the activity of MAO in platelets, research of Arato *et al.* [21] has shown that type O individuals have the lowest activity of this enzyme. The lower activity of this enzyme found in Type O's will make it harder for them to break down an excess of catacholamines. Craig *et al.* [22] investigated a human complementary DNA clone for dopamine beta hydroxylase that was isolated from a phaeochromocytoma library, and discovered the structural gene for the enzyme is located close to the ABO blood group locus.

ABO blood type has been known to play a significant role in the types of stress hormones we produce, their resting levels, the way we respond to stress, and how quickly they recover from stress. Locong & Roberge [23] looked at the levels of cortisol made in response to venisection. They considered very act of getting the blood drawn to be a mild physiologic stress, and then simply went about analyzing what was in the vacuum blood draw tube. After venisection, serum cortisol concentration (mean +/- SD) was found highest in blood group A donors (455 +/- 217 nmol/L), followed by group B (364 +/- 206), AB (325 +/- 154) and O (297 +/- 110). Blood group A individuals responded to a stressful situation with higher levels of cortisol, and possibly of adrenaline. These observations tend to support findings of previous studies demonstrating a high risk of diseases related to stress (coronary heart diseases), in men with A blood group.

We also performed additional analyses about the effect of gender or dominant hand with our experimental data. However, there was no statistically significant feature related with them.

Our experiment is simple and there is no complex procedure that is required to participants. However, our result may not indicate perfect features between each blood-type because the number of subjects was small. For the future work, we consider to conduct four-class classification because pairwise classification of ABO blood type may have few significance.

5. Conclusion

In the present study, we examined blood type–related differences in EEG signals that were measured from four scalp electrodes. The results of power spectrum analysis, ANOVA, and SVM classification showed significant distinguishable features in EEG signals among ABO blood types. They seem enough to analyze our current experimental data, but we will consider more analysis methods for the future works. Also, we will take into consideration advanced experiments with a large number of subjects and multiple EEG electrodes to identify the relationships between EEG and blood type.

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