Intern. J. Neuroscience, 115:781–802, 2005

ISSN: 0020-7454 / 1543-5245 online
DOI: 10.1080/00207450590881975

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UNCONSCIOUS OPERANT CONDITIONING IN THE PARADIGM OF BRAIN-COMPUTER INTERFACE BASED ON COLOR PERCEPTION

ALEXANDER YA. KAPLAN

Department of Human Physiology
Biological Faculty, Moscow State University
Moscow, Russian Federation

JONG-GIL BYEON

Chungbuk National University
School of Electronic and Computer Engineering
Chungcheongbuk-do, Republic of Korea

JONG-JIN LIM

Neuro-Telemetry Team
Lims Technology Co. Ltd.
Taejon, Republic of Korea

KYUNG-SOO JIN

Chungbuk Provincial University of Science and Technology
Department of Electronics & Information
Chungcheongbuk-do, Republic of Korea

BYOUNG-WOO PARK

Chungbuk National University
School of Electronic and Computer Engineering
Chungcheongbuk-do, Republic of Korea

Received 29 June 2004.
Address correspondence to Alexander Kaplan, Ph.D., Professor, Head of Human Brain Research Group, Biological Faculty, Moscow State University, 119992, Moscow, Russian Federation. E-mail: akaplan@mail.ru

SOFIA U. TARASOVA

Department of Human Physiology
Biological Faculty
Moscow State University
Moscow, Russian Federation

This study investigate the mutual fine-tuning of ongoing EEG rhythmic features with RGB values controlling color shades of computer screen during neurofeedback training. Fifteen participants had not been informed about the existence of neurofeedback loop (NF), but were guided only to look at the computer screen. It was found that during such unconscious NF training, a variety of color shades on the screen gradually changed from rather various types to the main one within the framework of color palette specified for each individual. This phenomenon was not observed in control experiments with simulated neurofeedback. Individual color patterns induced on the screen during NF did not depend on the schema of connection between of EEG rhythms and RGB controller. It is suggested that the basic neurophysiological mechanism of described NF training consists of the directed selection of EEG patterns reinforced by comfortable color shades without conscious control.

Keywords brain-computer interface (BCI), color perception, electroencephalogram (EEG), neurofeedback (NF), RGB model, spectral measures

INTRODUCTION

A Brain Computer Interface (BCI) is a communication system in which messages or commands that an individual sends to the external world do not pass through the brain's normal output pathways of peripheral nerves and—as defined by Wolpaw et al. (2002).

A BCI implements measurable electrical signals from the brain to a control or communication system. Measurements may be noninvasively taken from the scalp, resulting in an electroencephalogram (EEG). In the future, BCI system will monitor brain wave activities in real time and allow humans to use them for controlling any electronically addressable device or software through a local processor.

In the late 1980s and early 1990s, the field of BCI began to emerge in Europe and United States—driven by the idea of solving the communication problem of many disabled people by the use of an available power computer.

The essential part of BCI development is well known as the neurofeedback (NF) regulation first described by Kamiya (1968). It was shown in study of Kamiya and in many further investigations that humans can operate their parameters of EEG if these parameters are seen on the screen and reinforced with the appropriate reward such as scores, money, or simply encouraging words.

The main mechanism of NF is the operant conditioning paradigm where users learn to influence the electrical activity of their brain. EEG rhythm training that is suitable to both healthy and clinical populations is traditionally viewed as useful in a relax induced technique, originally associated with Zen meditation (Kassamatau & Hirai, 1969). It is also in reference to pathologies characterized by dysfunctional regulation of cortical activity, such as epilepsy forming part of a anticonvulsant therapy (Sterman, 1974; Kotchoubey et al., 2001) and attention deficit hyperactivity disorder in children (Linden et al., 1996; Lubar et al., 1997; Egner et al., 2001). Usually healthy individuals are capable of increasing their theta/alpha ratios after only five sessions (Egner et al., 2002).

Thus, if the person can operate parameters of his or her own brain activity, these parameters can be used as managing or triggering signals for different kinds of external devices. The central idea of Brain–Machine collaboration is to use EEG parameters not for the control of these parameters per se, for example to improve the health, but for the management of external objects previously connected with these parameters by means of a special interface named BCI.

Basically, a BCI provides new non-muscular and non-nervous channels for sending messages and commands to the external world. In the authors' opinion BCI is not only a brand-new neurologically based technology for clinics, but a new paradigm in neuroscience that can reveal previously unknown brain possibilities to develop the behavior "without nerves and muscles" and to integrate the person into new "thought driven" reality. The user has to only concentrate on some mental images that reflect a stable pattern in EEG and BCI will recognize this pattern as a command to previously fixed action: such as switching on the light or wheel-chair moving, and so on.

BCI has some applications within the medical community, for example, for locked-in patients who have no possibility to use their muscles (Hinterberger et al., 2003).

Unfortunately until now it was very difficult to use BCI systems both for disabled people and for healthy individuals. For example, one of the best BCI system, called Thought Translation Interface (TTI), takes more than several months to get very modest results, even by highly motivated users (Birbaumer et al., 1999, 2003).

In the authors' opinion, the main problem with contemporary BCI paradigms for users is the necessity to keep their mental states of concentration constant on the inner images or other kinds of mental states that have specific reflection in EEG patterns well recognizable for BCI. The operations with external objects in BCI paradigm are becoming not easier than, for example, piano playing or bicycle riding with constantly thinking how to move fingers or legs.

Fortunately after some training almost everybody is able to play piano music and ride on the bicycle automatically, that is, without conscious control. This process is known as automation during motor skill acquisition (Etnier et al., 1996; Ioffe, 2003). Different sets of brain regions are responsible for behavior before and after automation (Petersen et al., 1998; Honda et al., 1998). But unfortunately the automation does not occur in people even after some years of training in BCI paradigm with the greatest motivation to do so (Neuman, 2003).

The authors believe that the main reason for such poor automation process in contemporary BCI paradigm is double indetermination between the object of conditioning as visible realization of EEG signals (e.g., moving the cursor on the screen) and the reward as conscious evaluation of success trials.

First of them is the absence of definite determination between conscious intention of users for getting definite mental states (images) and result of this process. The second one is the lack of definite connection between even simple motor imagery (Cincotti et al. 2003) and the resulting EEG patterns, let alone more complex images (Curran et al., 2004; Kosslyn & Thompson, 2003). As a result the user cannot evoke the same EEG pattern every trial and BCI cannot properly recognize the user's intentions.

One of the approaches to overcome this problem is to refuse conscious control of feedback information in the BCI paradigm. At first glance, such an approach seems impossible because the user loses positive reinforcement that would come after a successful trial for conscious evaluation. Indeed in classical scheme of NF, the feedback gives back indifferent signals to users such as moving the cursor on the screen and the only previous instruction allows the participant to transform this signal in reinforcement reward.

Basically unconscious reinforcement reward is possible only in the case of active influence of feedback signal per se without previous knowledge. In this case, the user could automatically try to keep only comfortable for him the feedback signals and reject the undesirable ones if he could manage BCI without conscious control.

Thus the user will automatically select mental states suitable to operate the BCI system. The authors believe that after training procedure the user could automatically use this unconscious mental state as brain unconscious commands for BCI system. This is the key idea of their approach to developing the new paradigm for BCI systems.

The objective of the present study was to investigate the possibility for the operant conditioning of EEG patterns on humans on subconscious level. This study used the color as the information carrier in the feedback channel of BCI, basing this on the old idea (for review see Luscher, 1983) that surrounding color can modify mental state in definite direction on subconscious level. This conception also says that when a person chooses preferable color background or color card he or she involuntary tends to the color conditions, which could influence his mental state. Together with some other authors, the present authors believe that the choice of color spectrum is the feeling language of humans acquired from childhood (Burkitt et al., 2003).

It was hypothesized that color back signaling has unconscious reinforcement effects in the NF paradigm and color-induced patterns of EEG can be used as managing signal for BCI systems. The concrete aim of the present work was to investigate possible directional changes in dynamical EEG patterns during NF training with color back signal. Positive reinforcement by comfortable color has to lead to more frequent occurrences of corresponding EEG patterns. On the contrary, the negative reinforcement by aversive shades of color will result in reduction or even to disappearance of corresponding EEG patterns.

This article describes the processes of adjustments of color and EEG features during implicit learning in BCI paradigm. This article emphasizes a contour of the way for operating BCI automatically without conscious control and consequently the possibility to express human feelings through BCI as natural as it occurs when playing piano.

MATERIALS AND METHODS

Participants

Fifteen undergraduate and postgraduate students (male, aged 19–28 years: M = 22.1, SD = 2.9) were recruited for the study. All neurofeedback participants remained naive as to their specific aims of study until being fully debriefed at the end of the training program. All participants were right-handed, had normal or corrected-to-normal vision and approximately the same Walneffer coefficient according to the Luscher Color Test (Luscher, 1983), that is, degree of similarity with the multicolor choice in control rest conditions. The authors selected only participants with normal expression and gradient of EEG alpha-activity. The study was approved by the Research Ethics Committee.

EEG Registration

EEG was recorded with one scalp electrode placed on the skull at the right parietal position (P4, 10–20 system) referenced to the linked ears with ground electrode at the Fpz. Additionally four facial Ag/AgCl electrodes were employed to measure eye movements from which horizontal and vertical electrooculograms (EOG) were derived. These electrodes were positioned at the left and right outer canthi and approximately 1.5 cm above and below the left eye. The EOG measures were obtained for identification of ocular artifact and big saccades. All electrode impedances were below 5 kOm.

The analog EEG signals were amplified, analog-to-digital converted (sampling rate 128 Hz, 12-bit resolution) with bandpass of 0.5–30 Hz (6 dB/octave) and in on-line mode pass to the BCI system for feature extraction and EEG pattern classification (see later).

This article concentrates on one quantitative EEG feature set: power spectral density (PSD, uV^2) within theta (4.0–7.0 Hz), alpha (7.5–12 Hz), and beta (16–22 Hz) frequency bands. The EEG was converted from the time to the frequency domain using a fast Fourier transform (FFT).

General Procedures

The subjects were seated in a dimly lit room in comfortable chairs at a distance of 60–70 cm from the SVGA monitor (21 inches) on which the feedback by color signaling was presented with brightness comfortable for participants. They were in an awake condition but without any specific mental task. They were only told to take a comfortable position and to look at the screen without a definite purpose and even without precise focus on the screen.

There were 15 EEG recording trials, each 2 min, divided by 2 min breaks, covering three conditions: reference (RE), neurofeedback (NF) and mock (MK). The procedure always started with three RE trials: RE1, RE2, and RE3. Subjects simply would look at the black screen during RE condition. Then after a short break, the EEG was recorded in NF and MK conditions randomly following one after another for each subject. Therefore subjects # 2, 5, 6, 9, 10, 12, 13, 15 were tested in NF condition at the beginning and after that in MK condition, and on the contrary order for other subjects. Time for rest between NF and Mock procedures was about 10–15 min.

During biofeedback procedure all data were inspected automatically to remove the segments of EEG in which the ocular or muscle interval occurred from the normal ones. NF condition consists of 6 trials for 2 min EEG registrations each. During each NF trial, the subject was asked simply to look at the screen to determine which color was changing allegedly in random order. Actually, during NF condition, the color of the screen depended on individual features of on-line EEG (see later).

The authors selected RGB color model for numeric values to control colors on the computer screen by EEG features. FFT-based power spectral density (PSD) estimates of three EEG frequency bands (3-D vector) for sliding 2-s epochs (overlapping 75%) were calculated in on-line mode. Each short term 3-D PSD vector taken during NF trial was subtracted by average 3-D PSD vector of RE conditions, which was previously calculated off-line. The subtraction spectra (Kaplan et al., 1998) or 3-D subtracted PSD (sPSD) was used to manage the RGB controller: deviation of R, G, and B components on both sides from the middle RGB value (128, 128, 128—moderate gray) depended on percentage changes of the epoch PSD theta, alpha, and beta power in EEG in relation to the average level of EEG recorded earlier on the same subject during RE condition. The factor of signal transfer in brain–computer interface corresponded to the formula: 1% of PSD changes in EEG were equated to 3 levels of RGB changes. For example, if the regular epoch of EEG is changed in theta, alpha, and beta on +10, –5 and + 7% accordingly, the current screen color was defined in RGB model as 128 + 30 = 158, 128 – 15 = 113, 128 + 21 = 149. Therefore the maximal (255) and minimal (0) values, for example, for R component of RGB model, could be reached by changing theta power bands on 128/3 = 43% to one or opposite side.

The protocol of the MK condition was the same as NF for the subject one with only difference that the subject's EEG was not connected with the brain–computer interface. The RGB controller of computer screen in MK condition was managed by standard EEG, recorded previously from another subject during real NF condition.

Off-Line Analysis of Obtained EEG Data

One minute artifact-free EEGs were selected by visual editing of the continuous EEG that was recorded in each of all three trials of RE condition and in *last three trials* of NF and MK conditions. Therefore for each subject, 3 min EEG records were selected for each condition. For these EEG records, FFT-based 3 sets of subtraction PSD vectors were prepared for each subject using average PSD for RE period for a deducted factor. Each set of subtracted PSD contained 351 sPSD vectors. To test the hypothesis that a subject's EEG would be directly changed during NF condition, the authors searched the dominant subset of sPSD vectors that could determine the main tendency of EEG changes. The authors applied cluster analysis to each set of subtractive PSD vectors to do so.

The authors selected the *K*-means clustering algorithm. Whenever clustering is performed, the question of the optimum number of clusters is raised. It is well established in the literature that there is no universal solution to this question. Because of the rather high level of single spectrum variability, the authors decided to use a fixed number of clusters, to be used for all conditions and all subjects. Taking into consideration that each set of sPSD vectors for RE, NF, and MK conditions consist of 351 vectors (for 3 min of EEG observation 117 vectors each) and after examination of many clustering results, the authors decided to use 5 clusters for each set. In order to ensure that 3 different frequency components of spectra play an equal role in the clustering procedure, all feature changes were normalized to the percentage scale by dividing all values of each feature by the average value for reference set of spectra. Because there was only a rather small number of sPSD vectors in the testing set and high dynamical range of EEG events, the existence of outlines can strongly affect clustering results. This is why the authors eliminated 3% vectors of most prominent vectors at the beginning of final clustering procedures.

The authors compared the averaged 3-D PSD vectors of the biggest clusters between 3 conditions. Corresponding measures of EEG patterns in different conditions were compared using Student paired *t*-test at the one-tailed $p < .05$ level.

EXPERIMENTAL RESULTS

Experiment 1

Table 1 demonstrates the group average number of sPSD vectors in the biggest clusters for each of three conditions of EEG recording: RE, NF, and MK.

Table 1. Number of sPSD vectors in the greatest clusters in % of total number of sPSD vectors in all five clusters for each of three conditions of EEG recording: RE, NF, and MK

	RE	NF	MK	RE-MK	NF-MK
N% of sPSD	52 ± 3.8	53 ± 3.6	39 ± 3	$p < .05$	$p < .05$

Among 5 clusters that have expectations of 20% each, there is the biggest cluster containing about 52 and 53% sPSD vectors during Reference and NF periods and slightly less (on 12–13%, $p < .05$) during mock training. Therefore, the authors used the most frequent cluster for the evaluation of NF process because other clusters each contained no more then 12–15% vectors.

The test hypothesis was that, if the characteristics of the biggest cluster of EEG spectra are different when a subject's EEG controls the monitor color when compared with mock procedure, the active NF process starts even if subject does not realize it. The investigator can also actually observe this process if color of screen changes systematically from gray in NF condition to other colors.

The hypothesized EEG changes during NF condition were assessed by comparisons (paired t tests at one-tailed $p < .05$ levels) with RE and MK conditions. Descriptive statistics of all comparisons are presented in Table 2 as mean percentage changes in EEG power spectra during NF condition with comparison to Reference and Mock conditions. Only statistically significant results are presented in Table 2.

As can be seen in Table 2, for 15 subjects, the hypothesized significant changes (paired t tests, $p < .05$) for three EEG frequency bands during passive NF condition are reflected in 78% and 73% comparisons if compared with reference and mock condition. And only in 24% of cases were significant changes detected between Reference and Mock conditions (Table 2). In 9 of 15 subjects the significance EEG changes were found simultaneously in three frequency bands (Table 2).

To get more vivid results, the authors recalculated average subtraction spectra for greatest spectrum clusters in RGB scale according to ratio of: 1% of changes in EEG spectrum equivocal to shift in 3 RGB levels (see Methods) and presented it as average RGB codes (Table 3).

Table 3 shows the results of difference between three conditions: RE, NF, and MK. The notation used for the N% column indicates the number for RGB vectors (%) in the biggest cluster for each person and period of testing.

Table 2. Means for EEG changes in three frequencies bands of greatest cluster during NF and Mock conditions concerning Reference [(NF-RE) and (NF-MK)] condition and during Mock condition concerning Reference condition (MK-RE)

	NF–RE (%)			NF–MK (%)			MK–RE (%)		
Subjects	Theta	Alpha	Beta	Theta	Alpha	Beta	Theta	Alpha	Beta
1		–10			–10				
2	43	–16	–23	34	–8	–23	10	–8	
3	–13	19	–16		12	–21			
4									
5		11			10	–7			
6	34	–10	–24	37		–25			
7	32	32	–28	38	37	–21			–7
8	–27	16	–21	–22	18	–27			
9		10	9				10	10	9
10	38	–13	–30	25		–14	13	–8	–17
11	31		–25	33		–25			
12	29	–25	–7	26	–22				
13	–20	12	–7	–24	20	–10		–8	
14	20	–25	–10	13	–17	–9			
15	–18		–17	–22		–9			–8

Only statistically significant results (paired *t* test, one tailed $p < 0.05$ level) presented.

In the R, G, and B columns for RE, NF, and MK conditions, the values indicate the average RGB codes of biggest EEG spectra clusters for all three conditions. The shading color of each cell of three tables in RE, NF, and MK periods corresponds to the RGB code specified inside cells. That means, for example, that subject #3 produced mainly (64% of epochs) green-like color in NF condition whereas during reference period he produced (if connected with RGB controller) mainly grey-like color (71% of epochs).

Table 3 shows that only three subjects (1, 4, and 9) had no appreciable changes in screen color during NF procedure, and that means absence of changes in average EEG spectra of biggest cluster for NF condition. Other 12 subjects evidently manifested changes on the screen color during NF condition (Table 3). The authors divided these subjects into two well-recognizable groups: "Green"-like (subjects: 3, 5, 8, 13, 15), "Orange"-like (subjects: 2, 6, 10, 11), and one mixed group (subjects: 7—yellow, 12 and 14—"Violet"–like).

To get a more quantified picture of EEG-driven RGB changes during NF and MK periods the authors calculated them in 3-D space (Figure 1). For

Table 3. Average RGB Codes, managed by EEG spectral futures in NF conditions compared to RE and MK conditions (see notations in text)*

	Reference condition: RE1+RE2+RE3				Neurofeedback condition: RF4+RF5+RF6				Mock condition: MK4+MK5+MK6			
Subs	N%	R (Th)	G (Al)	B (Bt)	N%	R (Th)	G (Al)	B (Bt)	N%	R (Th)	G (Al)	B (Bt)
1	63	133	138	111	61	121	109	104	43	124	139	118
2	44	113	142	121	39	243	94	53	24	142	118	121
3	71	134	117	109	64	96	175	62	35	114	138	124
4	66	112	113	132	54	126	120	115	37	132	125	135
5	41	123	126	100	56	123	160	87	47	121	129	108
6	34	139	119	109	42	241	88	38	38	129	97	112
7	67	130	121	115	34	225	216	31	32	111	105	94
8	36	121	139	105	48	39	187	43	29	106	134	123
9	31	99	92	103	51	119	122	131	44	128	122	130
10	54	97	114	131	47	210	76	40	33	136	90	81
11	49	137	115	133	53	230	107	58	42	132	108	134
12	71	133	113	127	43	219	39	106	65	142	106	125
13	55	111	135	104	69	51	170	83	51	123	110	114
14	59	120	136	114	62	180	60	83	36	142	112	109
15	48	117	133	126	61	64	152	76	28	131	141	102

*See Color Plate IV at end of issue.

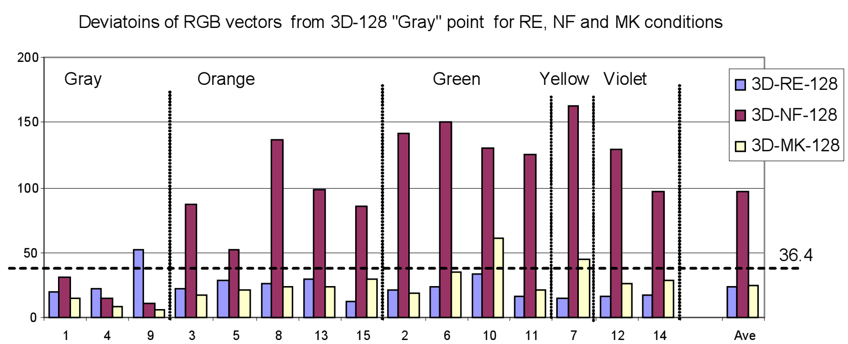

Figure 1. 3-D distances between RGB vectors managed by EEG spectral future in NF condition and the same vectors in RE and MK conditions for each participant (#1–14) grouped in Gray-, Orange-, Green-, Yellow-, Violet-like groups and in average (Ave) values. (See Color Plate V at end of issue.)

example, if each frequency band of EEG changes 7% (see Table 2), that is, each RGB component changes $7 \times 3 = 21$ levels, that resulting deviation in 3D space from the reference point (RGB: 128–128–128) will reach a value of 36.4. The authors used the radius 36.4 around reference point in RGB 3-D space as a threshold level to indicate that EEG really changed during NF conditions (Tables 2 and 3, Figure 1).

Only 2 subjects (7 and 10) demonstrated the EEG-RGB changes above threshold level (36.4) during Mock procedure in the average EEG driven RGB vector (Figure 1), which was not obvious to investigators if presented in color changes on the screen, as for NF period (Table 3).

Most of the subjects looked at the screen during mock period without any significant changes in EEG and as consequence—without color stabilization (Tables 2 and 3) on the screen. It was not connected with the size of biggest clusters of subtractive EEG spectra during Mock period because they were not significantly different from ones during reference and NF periods (no more than 12%, Table 1).

The authors could allocate EEG-RGB changes during NF procedure among 15 subjects (Table 3, Figure 1). Two big color groups: “Green-like” (subjects 3, 5, 8, 13, 15) and “Orange-like” (subjects 2, 6, 10, 11), and two smaller ones: “Violet-like” (subjects 12 and 14) and “Yellow-like” (subject 7). Three subjects (“Gray-like,” 1, 4, 9) demonstrated no evident changes in color on the screen during NF period.

The authors can note small variability in changes of the RGB codes between subjects inside the groups for greatest cluster of EEG spectra (Figure 2). Probably concerning preferred colors all people can be subdivided into a rather small number of groups.

EXPERIMENT 2

Of the hypothesized color-mediated subconscious operant conditioning of EEG features; the expected EEG changes were confirmed by the current data. The authors found non-instructed color stabilization on the screen only during NF condition with comparison to reference period and NF simulation (MK condition). Furthermore, the fact that most subjects tended to stabilize to usually more comfortable or basic colors on the screen (green, orange, etc.) during NF condition reinforces the interpretation of effects as an intentional but subconscious process of operant conditioning.

Nevertheless there is a question whether the type of color stabilization depends on initial commutation of EEG frequency bands with the components

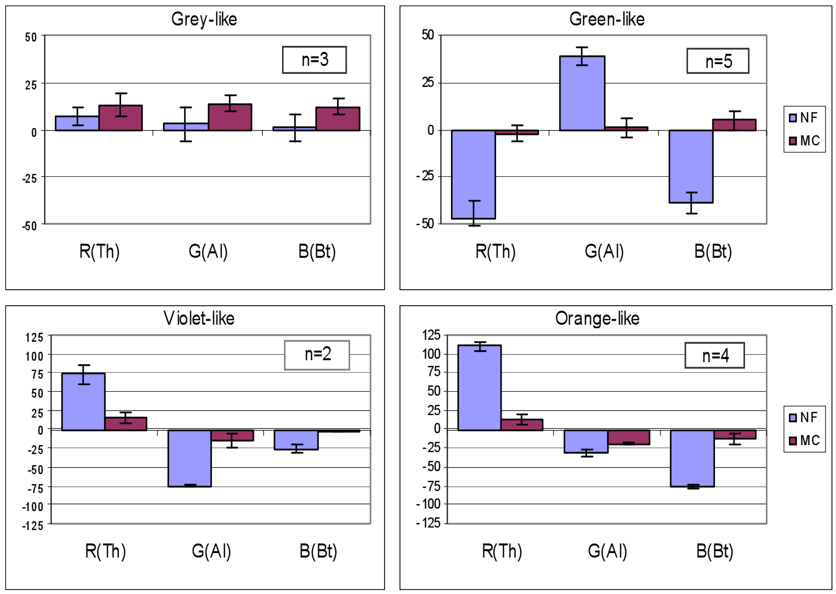

Figure 2. Group averaged changes of RGB codes (means ± SEM) during NF and MK conditions in comparison with RE condition. R(Th), G(Al) and B(Bt)—note the RGB code components driven by EEG rhythms (Th = theta, Al = alpha and Bt = beta). (See Color Plate VI at end of issue.)

of RGB model; also whether it changes the pattern of EEG stabilization if that commutation schema is reversed.

The authors selected subjects 2 and 6 from "Orange-like" group and subjects 8 and 13 from "Green-like" group to repeat the experiment with reversed alpha and theta bands commutation with RGB model components: "alpha—R" and "theta—G" instead, which is the opposite composition used in Experiment 1.

Table 4 shows that all four subjects kept style of color modulation on the computer screen in Experiment 2 during NF procedure, despite the reversed alpha and theta connection with RGB controller. However, within given color shade, the concrete RGB codes differ slightly between Experiment 1 and 2 (Table 4). The question is whether these differentials are casual or not. More precisely these distinctions can be considered in a 3-D RGB space separately for the RE and NF conditions (Figure 3). The 3-D distances between RGB codes in the 1st and 2nd experiments during RE condition can serve as an incidental level of differences.

Table 4. Average RGB codes, managed by EEG spectral futures in NF conditions compared to RE and MK conditions in Experiment 2 after commutation schema between EEG spectral features and RGB components was changed (see notations in text)*

Experiment 2 (Alpha and Theta reversed for RGB)									Experiment 1			
Sub.	N%	R (Al)	G (Th)	B (Bt)	N%	R (Al)	G (Th)	B (Bt)	N%	R (Th)	G (Al)	B (Bt)
2	56	118	131	116	37	234	124	84	39	243	94	53
6	63	133	123	119	43	194	107	56	42	241	88	38
8	58	131	123	126	51	92	172	88	48	39	187	43
13	47	125	127	117	56	119	153	97	69	51	170	83

*See Color Plate VII at end of issue.

Figure 3 shows that the differences between the results of Experiments 1 and 2 for the same subject are appreciably higher than incidental. And these differences are more expressed for the subjects from "Green-like" group. However, those differences are much greater between individuals from different color groups ("green" and "orange"), noted in Figure 3 as average value for all between individuals combinations (av_ID). Thus, at any circuit of switching of EEG rhythms with RGB components each person shows the

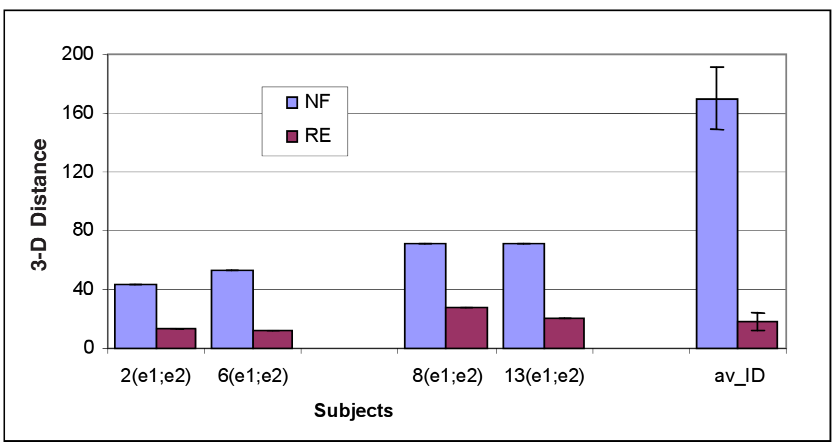

Figure 3. Individual differences between the results of Experiment 1 and 2 for RE and NF conditions and average level differences (av_ID) of between individual from different "color" groups. (See Color Plate VIII at end of issue.)

same individual tendency in unconscious preference of color during NF training (Table 3).

The most important fact is in order to keep this RGB pattern in Experiment 2 without principal deviations the considerable changes should take place in EEG pattern. This is illustrated by individual EEG spectra in two experiments. A typical realization of the average EEG spectra for Experiments 1 and 2 during RE and MK conditions are presented in Figure 4. FFT-based PSD estimates for the signals obtained by concatenating the EEG epochs belonged to the greatest cluster of EEG subtraction spectra in NF and MK conditions separately for 1st and 2nd experiments (Figure 4).

As can be seen in Figure 4, there are principal differences between EEG spectra during the same NF procedure in Experiments 1 and 2. These significances reflect greater alpha amplitudes and smaller theta amplitudes in subject's EEG during NF procedure in first experiment and all on the contrary in second one.

Therefore in general for Experiments 1 and 2 the phenomenon that 5–6 2-min sessions of color mediated unconscious operant training of EEG activity are sufficient to produce profound changes in a specific EEG frequency of individuals assessed objectively. The participants were able to selectively learn to modify their EEG activity by means of unconscious neurofeedback regulation. The second side of this phenomenon is objectively indicated in the ability of color to serve as subconscious reinforcement factor.

The fact that the 3 subjects (1, 4, and 9) failed to exhibit directional changes of color during NF condition when comparing to RE and MK con-

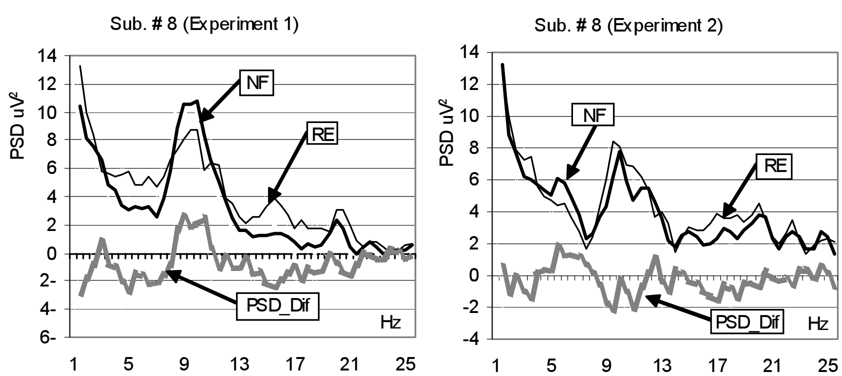

Figure 4. Average FFT-based PSD estimates for EEG epochs belonged to the greatest cluster of subtraction spectra in RE and NF conditions for subject #8.

ditions may be accounted for by the particular methodology used. Maybe, for instance, most comfortable tint for these three subjects was gray color. Thus, it was nothing to change for these participants because the gray color was adapted to starting EEG conditions.

DISCUSSION

Profound technological changes are sometimes caused by events initially considered to be completely irrelevant. Surprisingly, the first system of a neurofeedback was based on the color signal system. In 1971 Barry Sterman, who first describe the sensory-motor EEG rhythms (SMR), wired up his first human subject to a neurofeedback instrument. This unit was nothing more than a simple black electronic box with two lights on it, red and green. When the subject produced too much SMR the green light came on. When the subject was not in that range, a red light came on. So, the green light acted in Stern's experiments as the reinforcement reward because the user should keep the green color as long as possible during the training session according to the previous instruction (Sterman, 1972).

At the same time, according to the authors' everyday experience and experimental evaluations based on Luscher Color Test (Kertzman, 2003; Picco & Dzindolet, 1994), people favor green and blue when they crave peace and comfort. Probably the double combination of reinforcement rewards in Sterman's experiment of operant conditioning of SMR rhythms has made the first procedures of neurofeedback especially effective. Occasionally in these experiments outstanding results on therapy of epilepsy with the help of training SMR were received (Sterman, 1972). It was the first sure step of neurofeedback to many following clinical applications and for the improving of cortical processes in healthy individuals (for the review, see Sterman, 1996).

However, it is much more important in the authors' opinion that with discovering of the operant conditioning of the EEG patterns, the new paradigm in Neuroscience has been discovered. No one guessed the human brain's ability to express inner intentions out of natural brain outputs, nerves, and muscles. Even classical biofeedback with autonomic functions demonstrates the natural way of nervous circuits from brain through nerves to autonomic organs. It appeared that the brain can learn to operate with patterns of the cortical electric activity. It is a real opportunity for the person to transfer his internal intentions to outside environment without means of nerves and muscles, but only with the cooperation of EEG with BCI.

However, to achieve real progress in this area, it is necessary to study neurophysiologic mechanisms of operant conditioning of the EEG rhythms. Basically, it is rather obvious that the self-regulation of a physiological parameter is acquired according to operant conditioning principles. The question is which psychophysiological mechanisms would be involved in the acquisition of self-regulation of physiological parameters like EEG patterns in the frame of neurofeedback procedure?

In the case of biofeedback, it was suggested that participants consciously have to "perceive" a physiological function, like a heart rate, in order to control one (Brener, 1982). It becomes possible by presenting external feedback of the function's parameter as visual or acoustical signaling during internal sensations evoked by self-regulation of this parameter. The coincidences between events in external signaling and internal sensations during NF training lead to the creating of a mental "response image." Following Brener's hypothesis, the existence of acquired perceptible mental states or internal "response image" whose voluntary repeated activation leads to the production of the learned changes in the autonomic functions or EEG patterns should be offered.

However, it is especially important to emphasize that participants of neurofeedback procedure usually did not create and did not perceive consciously for those "response images" directly during operant conditioning. For example, patients, who had positive experience in the self-control of their EEG events, could explain their performance in detail, but only after they had already acquired the self-regulation. Thus the conscious perception and control of the "response images" most probably follow its automatic creation and not vice versa (Kotchoubey et al., 2002).

The major question arises: What are the neurophysiological mechanisms of the automatic or unconscious creation of "response images" during neurofeedback?

In the authors' opinion, the crucial process in the operant conditioning of the EEG pattern during NF, for example with color as rewarding signal, creates the specific quasi-stationary neuronal assembles or neuronal nets that can generate the EEG pattern that evokes most preferable color shades in NF procedure. The authors' previous findings showed that EEG can be consider a sequence of quasi-stationary patterns (Kaplan et al., 1999, 2001; Kaplan & Shishkin, 2000, 2001) particularly in a form of limited spectral patterns (Kaplan et al., 1998; Fingelkurts & Kaplan, 2003; Fingelkurts et al., 2003).

Taken together these findings, coupled with the new data, suggest the neurophysiologic mechanism of EEG conditioning in classical terms: correct behavior, discriminative, and rewarding stimuli. In BCI paradigm presented in this article, during display of the variety of color shade on the screen, as discriminative stimuli, those EEG patterns reinforced as correct behavior, which evoked only the most preferable color shade, as a rewarding stimulus. Apparently, in case of color-based BCI the shades of color are simultaneously discriminative and rewarding stimuli per se. And consequently they do not demand participation of consciousness in NF procedure.

Thus, the positive reinforcement by color shade automatically leads to a more frequent occurrence of an individual's correct behavior in the form of "correct" EEG patterns that are followed by comfortable color shades. On the contrary, the negative reinforcement of uncomfortable colors results in rare occurrence or disappearance of corresponding EEG patterns. This automatic procedure has good convergence because of rather limited repertoire of EEG pattern (Kaplan et al., 1998, 1999; Fingelkurtz & Kaplan, 2003). The authors' conception of automatic enumeration of EEG patterns or "EEG pattern selection" during NF procedure can be extended to the whole behavior in case of biofeedback. Indeed, they proposed earlier that described quasi-stationary EEG patterns in general cases reflect some kind of metastable brain states in different time and spatial scales (Kaplan & Shishkin, 2000). The same conceptions are stated by other investigators (Friston, 2001; Lehmann, 1998). Thus, there are objective neurophysiological prerequisites to suggest that EEG pattern selection or more deeply, neuronal ensembles selection mechanism lies in the basis of behavioral operant conditioning in neurofeedmack training. Lacroix and Gowen (1981) also supposed that limited patterns of different cognitive or behavioral strategies from the existing behavior repertoire is tested during neurofeedback until an aimed-for strategy for self-regulation is reached (Lacrous, 1981).

In common sense, the neuronal ensembles activity and corresponding EEG patterns selected by rewarding are the neuronal codes or models of significant external events and simultaneously are compact programs to manage external behavior. It is commonly accepted that people form mental models of tasks and external objects and these models are used to manage behavior as the two-side interface between inner intentions and external reality (Norman, 1993). These codes can be considered as preformed "macros" for the operation in perceptual and motor space. For example, the internal representations of movements are some kind of motor macros, stored possibly in the cerebellum (Ito, 2002).

The authors have assumed that in a course of BCI procedure a new kind of macros is developed according new output of brain actions. In particular, new cortical ensembles are created as macros that operate construction of corresponding EEG pattern for management of color shade on the display.

CONCLUSION

The authors have taken advantage of an old idea (for review see Luscher, 1983) about the existence of profound influence of color on human mental state for developing the BCI system with the active feedback loop without any conscious control. The BCI system in the present case not only passively "reads" the individual's EEG but also automatically reconstructs this ongoing EEG by selecting those patterns that can serve as some kind of "macros" for the management of comfortable color reality in the frame of BCI circuit. These findings confirm the authors' hypothesis that color signaling does have unconscious reinforcement effects in the NF paradigm and color induced EEG patterns can be considered as a managing signal for BCI systems such as indicating the emotional state of individuals without verbalizing one. It has allowed the authors to put forward the conception of automatic selection of quasi-stable cortical neuron nets, as one of the most probable neurophysiological mechanism of unconscious EEG operant conditioning.

The authors hope that the further optimization of the unconscious BCI training will provide tools for participants optimally to manage their cognitive and emotional resources by automatic self-regulation. It seems that we may be well on the eve of new changes in human–computer interaction, and these changes will be brought about by the recent development in the research methods of neuroscience. One of the actual spheres of share is so-called adaptive automation with the main aim to optimize Human–Machine cooperation in high workload situations (Prinzel, 2003). This sphere is still in a conceptual stage and a number of research issues still need to be addressed before widespread acceptance is possible.

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