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Neural Prediction of the Target "to BUY" or "NOT to BUY" by the ERP- based Cognitive BMI.

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Abstract: We have been developing an EEG-based cognitive brain-machine interface (BMI) system, Neurocommunicator® to support patients with severe motor deficits in communication. This system uses an event-related potential (ERP) to decode the message (pictogram) that users want to convey. In addition to the communication aid, it would be expected for the Neurocommunicator to improve the QOL of the users in a variety of daily-life situations. In this study, we focused on the brain activity that reflected the decision-making process of customers. We used the virtual shopping task as a model of daily shopping, in which a variety of product images were used as visual stimuli for the sequential delayed matching-to-sample paradigm. We recorded EEG data from 12 normal subjects and examined the ERPs in two conditions; the subject selected one (target) out of 8 products (nontargets) either "to BUY" (positive condition) or "NOT to BUY" (negative condition). We observed the strong ERPs not only to the target "to BUY" but also to the target "NOT to BUY" compared to the nontarget. The magnitude of the response and the decoding accuracy of the former were, however, greater than the latter. These results suggest that the ERP to a product is enhanced by the intention to buy it, and that the ERP-based Neurocommunicator has potential to become a "body-free" shopping tool for patients with severe motor deficits as well as a real-time neuromarketing/neuroconsulting tool for any person.
Keywords: *EEG, ERP, BMI, Neuromarketing, Neuroconsulting*

1. INTRODUCTION

There is recent world-wide interest in developing the brain-machine interface (BMI) [1], sometimes known as the brain-computer interface (BCI) [2], which provides a direct link between the brain and external devices. We have been developing the cognitive type of the BMI [3-4], "Neurocommunicator," which utilized the event-related potential (ERP) as a switch to select the desired message (pictogram) for patients with severe motor deficits in communication [5-7]. In addition to the communication aid, it would be expected for the Neurocommunicator to improve the QOL of the users in a variety of daily-life situations.

In this study, we focused on the shopping-related ERPs, and applied the Neurocommunicator to predict the item (the model of the product) that was the user's choice to buy. To examine the effect of the intention to buy on the brain activity, we compared the ERPs between two conditions, in which the user select the target either to buy (positive condition) or NOT to buy (negative condition). Here, we report the accuracy of the neural decoding of the target selection in the positive and negative conditions as well as the differences of the property of the responses between two conditions.

2. METHODS

2.1 Subjects and Behavioral Paradigm

We collected EEG data from 12 normal adult subjects under the protocol approved by the guideline and the committee of our institutes. To understand and utilize the neural basis of decision-making process about shopping, we presented a variety of stimuli as models of products. We prepared totally 64 items, which consisted of 8 each of 8 categories (groups) of products. We asked the subjects to make a ranking list of those categories from a viewpoint of the preference to buy in advance of the main experiment. We organized two experimental sessions (positive and negative sessions), the order of them was counterbalanced. While 8 groups of items of higher rank (1-8) were used as the visual cues in the 8 games of "positive" session, 8 groups of items of lower rank (9-16) were used as the visual cues in the "negative" session.

We used a Windows PC with an Intel Core-i7 class CPU to control the experiment as well as collect EEG data.

Keywords: EEG, ERP, BMI, Neuromarketing, Neuroconsulting

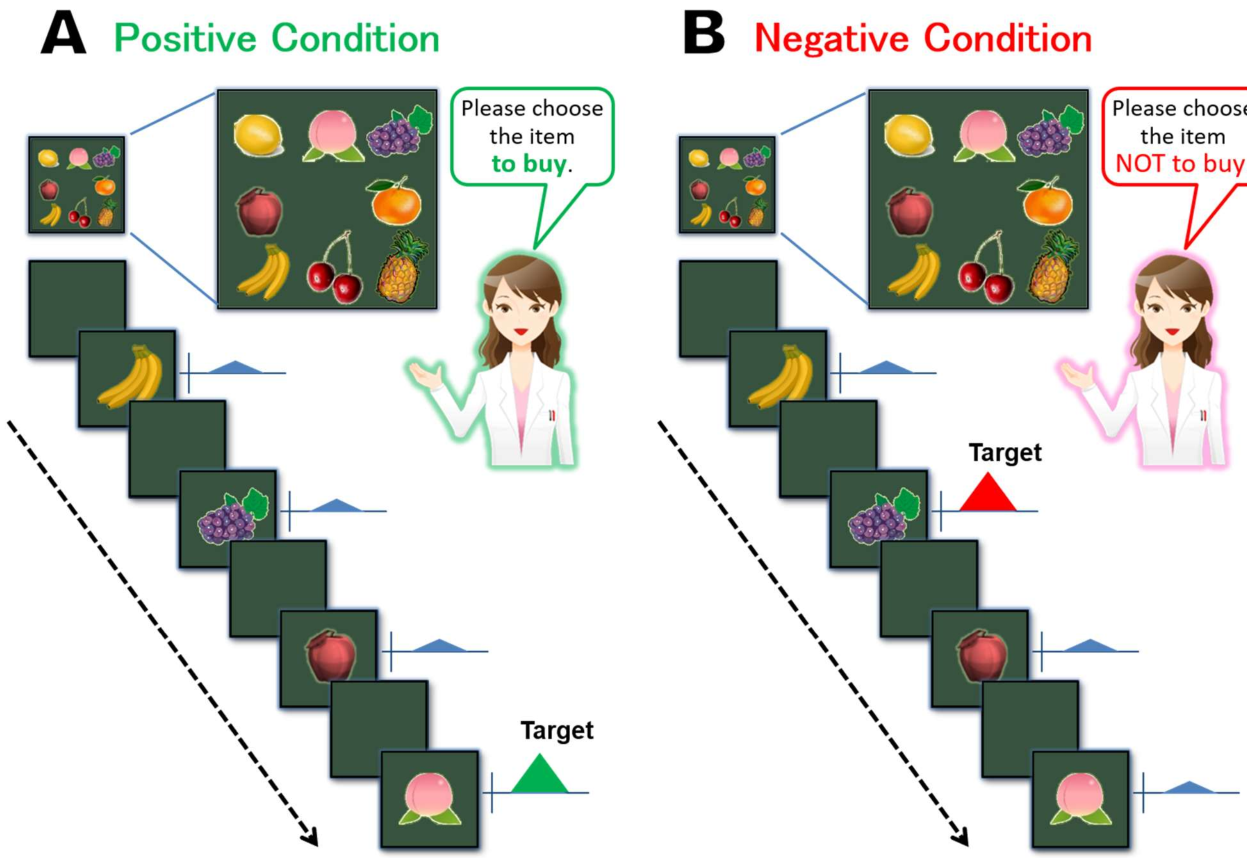

Figure 1: Schematic diagram of the virtual shopping task under the positive (A) and negative (B) conditions.

When each trial ("game") was started, the subject first selected, in their mind, one out of 8 items of each group as the "positive target" in the positive session (Fig. 1A) or as the "negative target" in the negative session (Fig. 1B). Then, these items were pseudorandomly presented one-by-one in a sequence (for 250 ms, separated by a 375 ms-blank), using a procedure of the sequential matching-to-sample task. Each game consisted of 9 blocks (repeats) of stimulus presentations. The subjects were asked to keep making a silent counting, though the game, either for the positive or negative target. After each game the subjects reported the ID number of the target, by wiring down it on the paper. The subjects took a break for 10 seconds between the games as well as for 5 minutes between the sessions.

2.2 Recoding

EEG data was obtained by a custom-made recording system, in which a compact EEG amplifier was attached on a plastic headgear. The headgear localized the electrode positions around the top of the head; in this study positions of 8 signal electrodes (Ch.1@FC1, Ch.2@FC2, Ch.3@C3, Ch.4@Cz, Ch.5@C4, Ch.6@CP1, Ch.7@CP2, and Ch.8@Pz) and one earth (ground) electrode (@CPz) were selected in the 10 % (10-10) system. A common reference electrode was positioned on a neutral point (earlobe). While conductive gels were used for the 8 signal electrodes and the earth electrode, a disposable electrode with solid gel was used for the reference. Raw EEG data were measured at a sampling late of 256 Hz, bandpass filtered (0.2–30 Hz) and digitized as 16 bits per sample. The digitized data were, in real time, sent to the PC with a wireless transmission method. As a conventional procedure in Neuroscience to examine the effects of the attention (target or nontarget) and its reason (to buy or not to buy) on ERP, we compared the waveforms of the downsampled ERP (64 Hz) among conditions.

2.3 Decoding

We focused on the possibility of the prediction of the target by the ERP data as a tool of Neurotechnology. For this aim, the 8 channels of continuous EEG data were downsampled to 21.3 Hz of feature values after additional software bandpass filter 0.2–30 Hz) in the PC. Then those values were then aligned to extract the single-shot ERP (without averaging) associated with the onset of the presentation of the visual cue. As described above, all subjects completed both the positive and the negative sessions. We performed linear discriminant analysis (LDA) to generate a pattern recognition model after each session. The optimized LDA model was designated to produce a high score (+1 on average) for the target and a low score (-1 on average) for the nontarget. The accuracy of the prediction of the target was examined by a kind of cross-validations, the "leave-one-out" method, in which the prediction in individual games was made using the model generated by the data of remaining games. The item with the highest (accumulative) discriminant score was predicted as the user's internal choice (target). After the 8 games of a session, the "success rate" was computed by dividing the number of the successfully predicted games (0 to 8) by the number of total games (8) in each subject. Although we mainly focused on the success rate on the final (9th) block as the index of the accuracy of our system, we calculated the success rate on all the 9 blocks in order to reveal the progress of the accuracy.

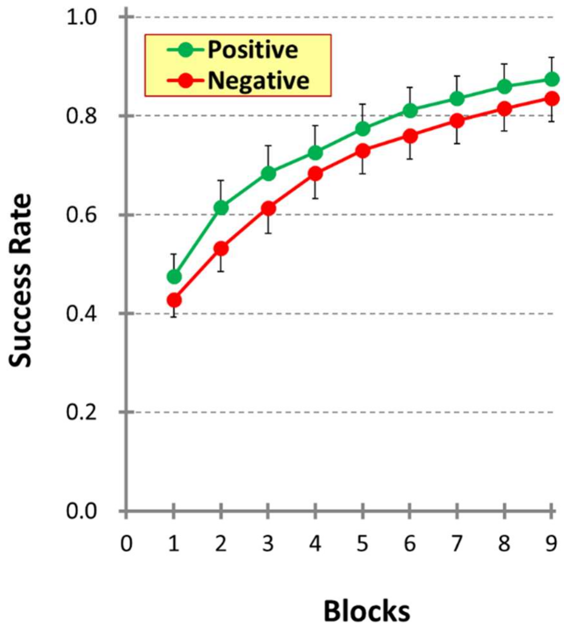

Figure 2: Accuracy of the prediction of the target.

3. Results

In this study, it was expected for the presentation of the target item to extract the ERP, which should be strong enough for the real-time prediction. Therefore, we first compared average ERPs to the target with those to the nontargets in positive and negative sessions. The response to the target was typically stronger than that to the nontarget, showing two positive peaks around 250 ms and 400 ms, to some extent, at all electrode positions. Then, we also compared the response to the target between two shopping (positive and negative) conditions. The magnitude of the response to the positive target was greater than that to the negative target. Finally, we compared the decoding accuracy (success rate to predict the target) between those conditions; although the accuracy under the both conditions gradually increased in blocks (repetitions of the pseudorandom presentation of a set of 8 stimuli), the positive target was higher than that about the negative target (Fig. 2). Two-way ANOVA indicated significant ($P<0.05$) main effects for shopping conditions and blocks.

4. Discussion

Neuromarketing is expected to reveal the neural basis of the decision-making processes of consumers that reflect both a conscious and unconscious intentions to purchase products. It is, however, still unclear how such an intention is represented by brain activity. Recently we have been developing EEG-based neuromarketing tools, using our custom-made BMI system, the Neurocommunicator [8-10].

In this study, we recorded EEG activities from the normal subjects during a cognitive task as a model of shopping behavior in order to explore the neural indicator of the intention to buy. We observed the strong ERPs not only to the target "to BUY" but also to the target "NOT to BUY" compared to the nontarget. The magnitude of the response and the decoding accuracy of the former were, however, greater than the latter. These results suggest that the ERP to a product is enhanced by the intention to buy it, and that the ERP-based Neurocommunicator has potential to become a "body-free" shopping tool for patients with severe motor deficits as well as a real-time neuromarketing /neuroconsulting tool for any person

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