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Experiences & Perspectives

Electrophysiological (EEG) Correlates of Reward Effects on Early Sensory Perception in Humans

Neuroscience, Signal Processing and Psychophysics

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Abstract

Existing research suggests that the reward system and sensory perception networks operate in concert and that activation in one can influence the other, but the dynamics of these influences remain poorly understood. There is general agreement that there is an interaction between bottom-up and top-down signals in perception and attentional processing. Although it's not entirely clear which stages of perception are influenced by cognition, it has been assumed that cognitive input influences later categorization stages of visual processing, and that earlier stages are involved only in the pure bottom-up extraction of basic features of sensory signals. Several recent experiments have challenged this idea by showing that top-down modulation by cognition can extend to early visual stages of perception. Recent electrophysiological studies have begun to investigate the neural correlates of the interaction between attention/reward, perception and cognitive control in humans. We propose that the selection of the value of our choices and actions from multiple alternatives may lead to the suppression of the sensory representations of unselected, low-value stimuli, while the selected, high-value stimuli are enhanced. The present project has been proposed to investigate the dynamics of this selective process by tracking the effects of different reward categories on attention and early sensory perception using behavioural and electrophysiological (EEG) techniques. Methods from neuroscience, signal processing, psychophysics and EEG tools will be used in the project.

Keywords: Perception; brain reward system; EEG; sensory; cognition

Resum

Les investigacions existents suggereixen que els sistemes de recompensa i les xarxes de percepció sensorial funcionen conjuntament i que l'activació d'una pot influir en l'altra; no obstant això, la dinàmica d'aquestes influències encara no es coneix bé. Hi ha un acord general sobre l'existència d'una interacció entre els senyals de baix a dalt i de dalt a baix en la percepció i el processament atencional. Tot i que no està totalment clar quines etapes de la percepció són influenciades per la cognició, s'ha assumit que l'entrada cognitiva influeix en les etapes de categorització posteriors del processament visual, i que les etapes anteriors estan involucrades únicament en l'extracció pura de baix a dalt de les característiques bàsiques dels senyals sensorials. Diversos experiments recents han desafiat aquesta idea mostrant que la modulació de dalt a baix per la cognició pot estendre's a les etapes visuals primerenques de la percepció. Estudis electrofisiològics recents han començat a explorar els correlats neurals de la interacció entre atenció/recompensa, percepció i control cognitiu en humans. Postulem que la selecció del valor de les nostres eleccions i accions entre múltiples alternatives pot causar la supressió de les representacions sensorials dels estímuls no seleccionats de baix valor, mentre que els estímuls seleccionats de gran valor són potenciats. El present projecte s'ha proposat per estudiar la dinàmica d'aquest procés selectiu on es rastregen els efectes de diverses categories de recompenses en l'atenció i la percepció sensorial primerenca utilitzant tècniques comportamentals i electrofisiològiques (EEG). Es faran servir mètodes de neurociència, processament de senyals, psicofísica i eines d'EEG en el projecte.

*Paraules clau***:** Percepció; sistema de recompensa cerebral; EEG; sensorial; cognició

Resumen
Investigaciones existentes sugieren que los sistemas de recompensa y de percepción sensorial funcionan en conjunto y que la activación en uno puede influir en el otro; sin embargo, la dinámica de estas influencias sigue siendo poco comprendida. Existe un consenso general sobre la existencia de una interacción entre señales ascendentes (bottom-up) y descendentes (top-down) en la percepción y el procesamiento atencional. Aunque no está completamente claro en qué etapas de la percepción influye la cognición, se ha asumido que la entrada cognitiva influye en las etapas posteriores de categorización del procesamiento visual, y que las etapas iniciales están involucradas únicamente en la extracción puramente ascendente de características básicas de las señales sensoriales. Varios experimentos recientes han desafiado esta idea al demostrar que la modulación descendente por la cognición puede extenderse a las primeras etapas visuales de la percepción. Estudios electrofisiológicos recientes han comenzado a investigar los correlatos neuronales de la interacción entre atención/recompensa, percepción y control cognitivo en humanos. Planteamos que la selección del valor de nuestras elecciones y acciones entre múltiples alternativas puede causar la supresión de las representaciones sensoriales de estímulos no seleccionados y de bajo valor, mientras que los estímulos seleccionados y de alto valor se realzan. Este proyecto ha sido propuesto para estudiar la dinámica de este proceso selectivo donde se rastrean los efectos de varias categorías de recompensa en la atención y la percepción sensorial temprana utilizando técnicas comportamentales y electrofisiológicas (EEG). En el proyecto se utilizarán métodos de neurociencia, procesamiento de señales, psicofísica y herramientas de EEG.

*Palabras clave***:** Percepción; sistema de recompensa cerebral; EEG; sensorial; cognición

Introduction

Every moment, we regularly experience sensory stimuli from our surroundings, from the feel of clothes on our skin, to the change of a traffic light from green to red, to the trilling of our mobile phone. These sensory stimuli are often also associated with a certain hedonic value, derived from our past experience of the positive or negative reward associated with them[20]. The reward associations of sensory stimuli are in constant motion, constantly changing as we unconsciously adapt to the many sensory changes that occur in our environment within a single moment[1,3]. We are constantly adapting our perception to the environment: deciding which rewarding stimuli are significant and planning our responses to these individual stimuli[7].

Neuroanatomical studies have shown that the brain's central reward pathway sends information to and receives information from many other brain regions[5,9,11]. The reticular activating system (RAS) directs arousal and attention to sensory inputs from our environment. Limbic regions such as the septum, amygdala and thalamus provide input to the reward pathway regarding emotional and motivational parameters[10]. The interaction of the reward pathway with the basal ganglia and cerebellum modifies the brain's motor function. Neurotransmitters are tracked and controlled by the hypothalamus. This command centre then transmits signals in the form of neurotransmitters to different areas of the brain[38].

Electrophysiological methods (such as single cell recordings) are widely used to elucidate how different reward systems influence sensory perception and action planning. Non-invasive variants of these methods, together with advanced data analysis techniques[39], allow proper investigation of brain function in humans. Electroencephalogram (EEG) is an example of these methods, allowing the measurement of neural activity time-locked to the presentation of stimuli and providing high temporal resolution and dynamics (on millisecond timescales)[11,12,22]. EEG recordings could also be performed simultaneously with measurements of hemodynamic changes in the brain, as in fMRI, which provides high spatial resolution (spatial resolution in millimeters)[4,25]. These methods are used in various psychological, behavioural and clinical neuroscience experiments[19,29,37].

The motivation of this review is to investigate how reward value affects early sensory perception in humans. Previous experimental and theoretical work has predicted that reward-based choices modulate responses in task-relevant perceptual and cognitive regions. This sensory modulation provides the system with the ability to enhance the representation of high reward stimuli relative to low reward stimuli, thereby supporting optimal adaptive behaviour in the face of changing stimulus-reward associations[27,30]. How might sensory processing be informed about the reward value of different stimuli? Bottom-up and top-down processes are used as effective solutions to the limited processing resources of the brain's executive system. Bottom-up processing of information is primarily informed by sensory input. In top-down processing, however, the brain allocates its resources based on behavioural goals and prior knowledge[2,13,32]. Previous research has shown that top-down processes robustly influence bottom-up processing, but the dynamics of these interactions during reward-based decisions are poorly understood. Here, we set out to investigate how top-down information about the value of different reward categories affects bottom-up sensory perception.

The primary goal of this research is to measure the effect of different rewards, including food, water, music, visual and auditory tasks, etc., on human perception. The second aim is to define the brain processing channels that are most frequently engaged in different cases of reward estimation tasks. Our main hypothesis is that different reward categories activate a common reward network, while each specific reward type selectively modulates its respective sensory brain area. The transmission of reward value from the common to the specific areas occurs via mid-level areas that represent both reward and sensory information. Crucially, we find that this transmission can occur by modulating response magnitude as well as by inducing oscillations in a specific frequency band. Using different types of reward allows us to identify the most commonly used 'code' that different brain areas use to transmit reward information across the brain.

The old study by Gilchrist and Nesberg in 1952 showed that hungry subjects overestimated the brightness of pictures of food compared to other pictures. Later, in 1957, Bruner's conceptual basis of the New Looks framework suggested that perception is influenced by top-down factors related to individual expectations and needs. In 1997, Breiter'sHuman studies of rewarding stimuli suggested that intensely pleasurable emotions are mediated by neural activity in neural systems through motivational, emotional (limbic) and arousal processes. In 2001, Anne J. Blood experimented with music rewards and found a link between physiological signals and the intensity of the music[6].Another line of evidence comes from combined behavioural and EEG studies that have investigated the dynamics of sensory processing. A study by Sophie Molholm in 2002 suggested that reaction time changes according to audio-visual neural interactions[23].Recent studies show that electroencephalography (EEG) provides a method to highlight the temporal characteristics of synesthetic experience in order to evaluate early sensory processing[5,16,24]. A recent experiment by Porbadnigk in 2013 used a machine learning approach on EEG data to investigate brain states in auditory perception[31]. Similarly, a number of studies have investigated the EEG correlates of perception in the visual modality (for a review see: Norcia et al.)[26]. A separate line of research has sought to investigate the neural correlates of reward processing in humans. Hagerty used both fMRI and EEG to investigate the reward system[14].Krigolson et al. 2013 showed that learning of reward associations in a gambling task is explicitly reflected in changes in evoked EEG responses to novel reward cues over time[17,21].Importantly, recent studies have shown that during perceptual tasks, sensory stimuli associated with reward elicit changes in evoked potentials or the oscillation patterns of EEG data[15,18] compared to unrewarded stimuli. These findings suggest that changes in the synchronous activity of distributed neuronal cell assemblies may underlie the effects of reward on perception. Our proposed idea of correlating EEG parameters with early sensory perceptual functions across different reward categories is inspired by this idea and is unique in its conceptualisation, falling within the latest trends in neuroscience research (for a review of the importance of elucidating reward effects on early sensory perception see[27,28]).

Materials and methods

The EEG signal analysis method is used in the case of reward effects on early sensory perception.EEG signal processing involves the following steps

• Data Acquisition

Recording

EEG signal recorded by wired or wireless recording systems on multiple channels as required by protocol or event.

Preprocessing

This step includes normalisation, digitisation and filtering. Normalisation is a very important step; it only minimises the scaling of the signal without changing its basic characteristics. The raw EEG data is filtered for noise induced by power line interference, EMG and EOG etc[33,34,36]. The task of filtering is carried out by implementing various filters such as band pass filters, low pass filters, high pass filters and adaptive filters depending on the quality of data and analysis requirements. Digitisation of data is done to convert the analogue data into digital data (however, it is not required in case of already digitised recording devices).Analogue signals are continuous and smooth. Digital signals represent discrete points in time and their values are quantities with a fixed resolution rather than those of continuous signals. Digitised signals are convenient for data analysis purposes[36].

• Feature Extraction

Extracting the relevant data from the digitised data that can be used for proper classification is an important step[8]. The extracted feature contains the useful information, therefore the accuracy of the feature extraction affects the accuracy of the classification. Feature extraction can be done in both time and frequency domain. Some examples of time domain analysis are common spatial pattern (CSP) evaluation, auto-regressive parameter estimation, basic probability and statistical analysis[34]. Some examples of frequency domain analysis are Fourier spectral analysis and power spectral density estimation. Data reduction can be achieved in the feature extraction process by selecting only the relevant data for classification.

• Classification

Once the correct features have been extracted, they need to be identified as a particular occurrence or class using classification algorithms[35,36].

• Source localization of EEG signals

The method of source localisation of EEG signals is used to localise brain activity; it provides useful information about physiological, psychological and functional abnormalities of the brain. This problem is called the EEG inverse problem[36].

Data collection analysis and evaluation

60-100 healthy subjects of different age groups, male and female, left and right handed, will be recruited to participate in studies on the effects of reward on perception through different reward systems. All subjects will be required to sign the informed consent form to participate in these studies. They may be asked to complete a questionnaire to establish their profile. Prior to the start of the experiment, the subjects will be given a training session to familiarise them with the do's and don'ts of the specific research protocol.

The normal baseline EEG parameters recorded will be compared with the EEG parameters recorded during or after reward-based decisions, so that the effect of reward learning can be assessed. Reward based decisions involve the presentation of different reward categories, with the subject indicating which stimulus they choose (by pressing a button). We compare EEG correlates (in the time or frequency domain) across different reward categories to identify those that are common across reward classes and those that are specific to each class.

Results

We expect that oscillations in a specific frequency band carry reward information throughout the brain, regardless of the reward category (visual or auditory). Sensory processing of each reward category will be selectively modulated when a perceptual judgement is required about another exemplar of the same category (but not the other categories). As a result of this research, we will be able to identify a general brain reward processing system across different reward categories. This is a crucial step in the development of strategies to enhance sensory performance and cognitive control in humans, for example where sensory processing is impaired (e.g. poor vision) or pathologically hypersensitive (e.g. in addiction).

Discussion

The environment is rich in different types of information. Sensory organs such as the eyes, ears, tongue, skin and nose provide sensory information such as light, sound, taste, touch and smell. This information not only informs the brain about the sensory properties of environmental stimuli, but also signals their associated rewards. In fact, these two types of information can influence each other, and behavioural studies have repeatedly demonstrated these interactions.

Conclusions

The general brain reward processing system will help us to understand the effects of different early sensory perceptions in human subjects. We will also test which of these EEG signals correlate with behavioural performance measured by reaction time and choice probability.

References

1. Abrams, D. A., Chen, T., Odriozola, P., Cheng, K. M., Baker, A. E., Padmanabhan, A., . . . Menon, V. (2016). Neural circuits underlying mother's voice perception predict social communication abilities in children. Proceedings of the National Academy of Sciences, 113(22), 6295-6300. doi:10.1073/pnas.1602948113
2. Awh, E., Belopolsky, A. V., &Theeuwes, J. (2012). Top-down versus bottom-up attentional control: a failed theoretical dichotomy. Trends in Cognitive Sciences, 16(8), 437-443. doi:10.1016/j.tics.2012.06.010
3. Balconi, M., Venturella, I., &Finocchiaro, R. (2017). Evidences from Rewarding System, FRN and P300 Effect in Internet-Addiction in Young People. Brain Sciences, 7(9), 81. doi:10.3390/brainsci7070081
4. Bandettini, P. (2015). Temporal Resolution and Spatial Resolution of fMRI.Brain Mapping, 173-182. doi:10.1016/b978-0-12-397025-1.00020-8
5. Barnett, K. J., Foxe, J. J., Molholm, S., Kelly, S. P., Shalgi, S., Mitchell, K. J., & Newell, F. N. (2008). Differences in early sensory-perceptual processing in synesthesia: A visual evoked potential study. NeuroImage,43(3), 605-613. doi:10.1016/j.neuroimage.2008.07.028

6. Blood, A. J., &Zatorre, R. J. (2001). Intensely pleasurable responses to music correlate with activity in brain regions implicated in reward and emotion. Proceedings of the National Academy of Sciences, 98(20), 11818-11823. doi:10.1073/pnas.191355898
7. Calvert, G. A., &Thesen, T. (2004). Multisensory integration: methodological approaches and emerging principles in the human brain.Journal of Physiology-Paris, 98(1-3), 191-205. doi:10.1016/j.jphysparis.2004.03.018
8. Chandra,S.; Verma K. L.; Sharma,G.; Mittal,A.; & Jha D. (2015), EEG based Cognitive Workload Classification during NASA MATB-II Multitasking, International Journal of Cognitive Research in Science Engineering and Education, 3(1),35-41.
9. Christoph, H. (2010). Gamma amplitudes are coupled to theta phase in human EEG during visual perception. Frontiers in Neuroscience, 4 doi:10.3389/conf.fnins.2010.06.00219
10. Davey, C. G., Allen, N. B., Harrison, B. J., Dwyer, D. B., &Yücel, M. (2009). Being liked activates primary reward and midline self-related brain regions. Human Brain Mapping. doi:10.1002/hbm.20895
11. Ebersole, J. S., & Milton, J. (2003). The Electroencephalogram (EEG): A Measure of Neural Synchrony. Epilepsy as a Dynamic Disease, 51-68. doi:10.1007/978-3-662-05048-4_5
12. Finocchiaro, R., &Balconi, M. (2015). Reward-system effect and "left hemispheric unbalance": a comparison between drug addiction and high-BAS healthy subjects on gambling behavior. Neuropsychological Trends,(17), 37-45. doi:10.7358/neur-2015-017-fino
13. Gilbert, C. D., &Sigman, M. (2007). Brain States: Top-Down Influences in Sensory Processing. Neuron, 54(5), 677-696. doi:10.1016/j.neuron.2007.05.019
14. Hagerty, M. R., Isaacs, J., Brasington, L., Shupe, L., Fetz, E. E., & Cramer, S. C. (2013). Case Study of Ecstatic Meditation: fMRI and EEG Evidence of Self-Stimulating a Reward System. Neural Plasticity, 2013, 1-12. doi:10.1155/2013/653572
15. Hajihosseini, A., &Holroyd, C. B. (2015). Erratum: Reward feedback stimuli elicit high-beta EEG oscillations in human dorsolateral prefrontal cortex. Scientific Reports, 5(1). doi:10.1038/srep14400
16. Hauser, T. U., Hunt, L. T., Iannaccone, R., Walitza, S., Brandeis, D., Brem, S., & Dolan, R. J. (2015). Temporally Dissociable Contributions of Human Medial Prefrontal Subregions to Reward-Guided Learning.Journal of Neuroscience, 35(32), 11209-11220. doi:10.1523/jneurosci.0560-15.2015
17. Heydari, S., &Holroyd, C. B. (2016). Reward positivity: Reward prediction error or salience prediction error? Psychophysiology, 53(8), 1185-1192. doi:10.1111/psyp.12673
18. Hughes, G., Mathan, S., & Yeung, N. (2013). EEG indices of reward motivation and target detectability in a rapid visual detection task. NeuroImage, 64, 590-600. doi:10.1016/j.neuroimage.2012.09.003
19. Iannetti, G. D., Hughes, N. P., Lee, M. C., &Mouraux, A. (2008). Determinants of Laser-Evoked EEG Responses: Pain Perception or Stimulus Saliency? Journal of Neurophysiology, 100(2), 815-828. doi:10.1152/jn.00097.2008
20. Kirsch, P., Schienle, A., Stark, R., Sammer, G., Blecker, C., Walter, B., . . . Vaitl, D. (2003). Anticipation of reward in a nonaversive differential conditioning paradigm and the brain reward system:. NeuroImage, 20(2), 1086-1095. doi:10.1016/s1053-8119(03)00381-1
21. Krigolson, O. E., Hassall, C. D., & Handy, T. C. (2014). How We Learn to Make Decisions: Rapid Propagation of Reinforcement Learning Prediction Errors in Humans. Journal of Cognitive Neuroscience, 26(3), 635-644. doi:10.1162/jocn_a_00509
22. Luck, S. J. (2014). An Introduction to the Event-Related Potential Technique. Cambridge, Masachusetts: Mit Press.
23. Molholm, S., Ritter, W., Murray, M. M., Javitt, D. C., Schroeder, C. E., & Foxe, J. J. (2002). Multisensory auditory–visual interactions during early sensory processing in humans: a high-density electrical mapping study. Cognitive Brain Research, 14(1), 115-128. doi:10.1016/s0926-6410(02)00066-6
24. Monteleone, E., &Dinnella, C. (2017). General Considerations. Time-Dependent Measures of Perception in Sensory Evaluation, 157-181. doi:10.1002/9781118991640.ch7
25. Muraskin, J., Sherwin, J., Lieberman, G., Garcia, J. O., Verstynen, T., Vettel, J. M., &Sajda, P. (2017). Fusing Multiple Neuroimaging Modalities to Assess Group Differences in Perception–Action Coupling. Proceedings of the IEEE, 105(1), 83-100. doi:10.1109/jproc.2016.2574702
26. Norcia, A. M., Appelbaum, L. G., Ales, J. M., Cottereau, B. R., &Rossion, B. (2015). The steady-state visual evoked potential in vision research: A review. Journal of Vision, 15(6), 4. doi:10.1167/15.6.4
27. Pessoa, L. (2010). Embedding reward signals into perception and cognition. Frontiers in Neuroscience, 4. doi:10.3389/fnins.2010.00017
28. Pessoa, L. (2014). Multiple influences of reward on perception and attention. Visual Cognition, 23(1-2), 272-290. doi:10.1080/13506285.2014.974729
29. Pooresmaeili, A., Poort, J., &Roelfsema, P. R. (2014). Simultaneous selection by object-based attention in visual and frontal cortex.Proceedings of the National Academy of Sciences, 111(17), 6467-6472. doi:10.1073/pnas.1316181111
30. Pooresmaeili, A., Fitzgerald, T. H., Bach, D. R., Toelch, U., Ostendorf, F., & Dolan, R. J. (2014). Cross-modal effects of value on perceptual acuity and stimulus encoding. Proceedings of the National Academy of Sciences, 111(42), 15244-15249. doi:10.1073/pnas.1408873111
31. Porbadnigk, A. K., Gornitz, N., Kloft, M., & Muller, K. (2013). Decoding Brain States during Auditory Perception by Supervising Unsupervised Learning. Journal of Computing Science and Engineering, 7(2), 112-121. doi:10.5626/jcse.2013.7.2.112
32. Sarter, M., Givens, B., & Bruno, J. P. (2001). The cognitive neuroscience of sustained attention: where top-down meets bottom-up. Brain Research Reviews, 35(2), 146-160. doi:10.1016/s0165-0173(01)00044-3
33. Verma, K. L. (2012). EEG Correlates of Cognitive Workload during Multitasking Work. ISBN: 978-3-659-30224-4. Lambert Academic Publishing, Germany.
34. Verma, K. L., Jaiswal, A. K., &Chandel, S. S. (2012). Statistical Methods of Bio-Physiological Data Processing. ISBN 978-3-659-31141-3. Lambert Academic Publishing, Germany.

35. Verma, K.L.; Jaiswal, A.K.; Mishra, M.; & Shukla, A.K. (2014). EEG Interface Module for Cognitive Assessment through Neurophysiologic Tests, International Journal of Cognitive Research in Science Engineering and Education, 2(2), 61-65.
36. Verma, K. L., Mishra, M., & Ve, V. (2012). A Survey of EEG Signal Processing Techniques. ISBN: 978-3-8433-6873-5. Lambert Academic Publishing, Germany.
37. Wang, P., Göschl, F., Friese, U., König, P., & Engel, A. K. (2015). Large-scale cortical synchronization promotes multisensory processing: An EEG study of visual-tactile pattern matching. doi:10.1101/014423
38. Wichmann, T., &Delong, M. R. (2011). Deep-brain stimulation for basal ganglia disorders. Basal Ganglia, 1(2), 65-77. doi:10.1016/j.baga.2011.05.001
39. Yamashita, M. (2014). Electrophysiological Recordings from Neuroepithelial Stem Cells. Methods in Molecular Biology Stem Cell Renewal and Cell-Cell Communication, 195-200. doi:10.1007/7651_2014_96