ISSN 1870-4069

How Objects Categorize the Human Brain: EEG and fMRI as Analysis Point

Rigoberto Cerino[1], Sergio Vergara[2]

[1] Benemérita Universidad Autónoma de Puebla,
Facultad de Ciencias de la Computación,
Mexico

[2] Benemérita Universidad Autónoma de Puebla,
Facultad de Ciencias de la Electrónica,
Mexico

{cerino_rigoberto, svergara2}@hotmail.com

Abstract. This paper aims to study the state of the art of research based on the reading and processing of brain signals, which allow categorization of different concepts, in multiple aspects, such as images or texts. An analysis of works that perform semantic classifications of objects such as houses, faces, tools, buildings is presented. Existing methodologies of the general process of reading and adaptation of brain waves, the types of filters implemented for the elimination of noise in the signals, and types of signal classifiers are exhibited. The study is oriented to non-invasive methods of brain wave reading, such as electroencephalography (EEG) through electrode headbands, and functional magnetic resonance imaging (fMRI).

Keywords. Categorization, classification, concepts, EEG, filter, fMRI, neuroimaging, semantics.

1 Introduction

The identification of the neural processes that underlie semantic representations is a key challenge in cognitive neuroscience. Different hypotheses have been proposed on how representations of particular concepts establish a conceptual knowledge system. The general acceptance is that the properties of shared objects are reflected in the organization of the semantic system and that the system is generalized through concepts that belong to a particular category (such as animals, tools or buildings). The notion of category specificity in the organization of object knowledge arose in the 1980s, when Warrington and his colleagues reported for the first time on patients with selective disabilities for a semantic category compared to other semantic categories [1]. Since these initial investigations, a large number of studies have confirmed the phenomenon of semantic deficits specific to the category.

It has been reported that patients have impediments to all kinds of knowledge about a particular category, such as living things, for example, [2, 3].

Differences in brain activity related to the category have been demonstrated with various neuroimaging methods in healthy subjects, for living beings versus man-made objects, and for various categories of specific objects, such as faces, body parts, animals, fruits, vegetables, buildings, tools and furniture [4-6]. For some types of objects, the functional organization by semantic category has been demonstrated within a given modality, for example, category-specificity in the visual path for faces [7, 8] or for living versus non-living entities [9, 10]. It has also been shown that objects and their sensory or functional attributes (such as actions associated with tools) activate the same neuronal regions [11, 12, 1], suggesting that these regions are implicitly involved in the conceptual representation.

Achieving a clearer picture of the categorical distinctions in the brain is essential for the understanding of the conceptual lexicon, but much more precise investigations both in categorical distinctions and in other aspects of the conceptual re-presentation [13, 14] will be necessary for this evidence contribute to lexical research. Although semantics clearly plays a central role in the ability of human language, since the transfer of meaning is the goal of a purposeful communication, our understanding of its instantiation and functional location in the brain is far from complete. These types of systems can have very specific applications in real life, for example, as support for people who lost speech, people who do not listen, people who have had a stroke and need to verify if the concepts are still present in their mind.

2 Representation of Object Concepts in the Brain

Object concept: “Memory representations of a class or category of objects. Necessary for numerous cognitive functions, including the identification of an object as a member of a specific category and making inferences about the properties of the object” [15].

Evidence of the functional neuroimaging of the human brain indicates that information about the outstanding properties of an object, such as its appearance, how it moves and how it is used, is stored in the active sensory and motor systems when that information was obtained. As a result, the concepts of objects belonging to different categories, such as animals and tools, are represented in neural networks based on partially distinct sensory and motor properties. This suggests that object concepts are not explicitly represented, but arise from weighted activity within brain regions based on properties. However, some property-based regions seem to show a categorical organization, thus providing consistent evidence with domain-specific formulations based on categories as well.

The central idea is that knowledge of the object is organized by sensory characteristics (Form, movement, color) and motor properties associated with the use of the object (and in some models, other functional properties, verbally measured, such as where typically finds an object, its social meaning, etc.) [5]. Most studies examine only distinctions in very distant semantic fields, for example comparing abstract and concrete concepts, verbs and nouns, or natural and artifact types [1, 10, 16-19].

Convergent evidence of monkey neurophysiology, neuropsychology and functional brain imaging has established that object recognition critically depends on the current of ventral occipitotemporal processing (see [20]). In addition, functional studies of brain imaging of object recognition have provided convincing evidence that the occipitotemporal cortex is not a homogeneous object processing system, but has a fine-grained structure that appears to be related to the object category. The most tested categories have been human faces, houses, animals and tools [1, 10, 16, 17, 19, 21-24]. The direct comparison of one category of object with another has revealed different activity groups (for example, the fusiform area of the faces, (FFA); the region of the brain called Parahippocampal Place Area (PPA) (Fig. 1). In addition, pattern analysis techniques have identified different activity patterns related to the category of objects that discriminate between a relatively large number of object categories [10, 25-31]. These patterns related to the category of objects extend over a large area of occipitotemporal cortex, are stable both within and between subjects, and can be identified even when subjects freely view complex scenes [32].

[33] provided evidence that category-related activity groups in occipitotemporal cortices associated with visualization of object images are also seen when subjects participate in a verbal conceptual processing task.

3 Conceptual Processing and Subsequent Temporal Cortex

Functional brain imaging studies on conceptual and semantic-lexical processing (that is, using word stimuli) have constantly isolated two key brain regions: left ventrolateral prefrontal cortex (VLPFC) and the ventral and lateral regions of the posterior temporal cortex, generally stronger in the left hemisphere than in the right (Fig. 1) [34, 35].

Activity in VLPFC has been strongly associated with semantic memory control; specifically, recovery guide and post-recovery selection of conceptual information stored in subsequent temporal areas and perhaps in other cortical areas [1].

A large amount of functional neuroimaging evidence has implicated the temporal lobes, particularly the posterior region of the left temporal lobe, as a critical site for stored representations, especially on concrete objects. Recent studies have provided additional support for this view by demonstrating that the regions of the left posterior temporal cortex that are known to be active during conceptual processing of images and words (fusiform gyrus and lower and middle temporal gyrus) (Fig. 1) were also active during the listening comprehension of the sentences [36-38].

Another recent approach to investigate functional neuroanatomy of conceptual processing has been to use stimulus repetition tasks. It is well established that previous experience with a stimulus results in a more efficient process (repetition primacy) and a reduced hemodynamic response, typically known as repetition suppression, but also as adaptation, neural primacy and repetition attenuation, when that stimulus is found later [39].

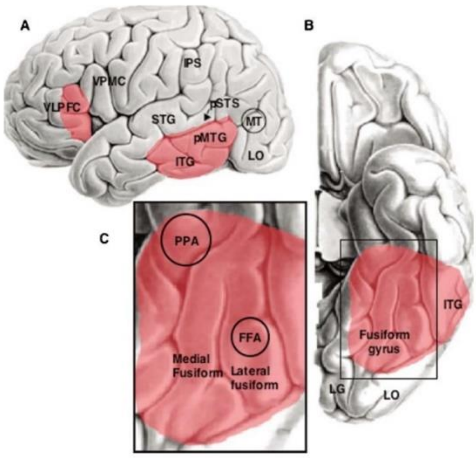

Fig. 1. Schematic lateral view of the left hemisphere (A) and ventral view of the frontal and right temporal lobes (B). The fusiform turn is shown in greater detail in (C). The red regions show the approximate location of areas typically involved in conceptual processing tasks, especially with specific objects. ITG, Inferior temporal gyrus; LG, lingual gyrus [5].

Activity patterns related to the category of objects have been observed in the ventral and lateral regions of the posterior temporal cortex using a variety of stimuli (images, written names, sounds associated with objects, names heard) [9, 39, 40].

The ventral temporal cortex shows strong category effects, but these effects were not modulated by movement. In contrast, the lateral temporal areas responded more strongly to the movement than to the static images, supporting the hypothesis that the lateral temporal cortex is the cortical site of complex motion processing.

4 Identification of Object Categories from EEG Related to Events

First, electroencephalography (EEG) has a well-documented ability to characterize certain brain states, in particular the processing of different semantic categories. Second, the high temporal resolution of the EEG allows an accurate characterization of the concept's recovery in terms of the electrophysiological patterns that make decoding possible. Thirdly, the development of semantic decoding algorithms based on EEG is interesting from the perspective of applications, since the temporal resolution of EEG allows decoding in real time. There are multiple pattern analysis techniques that allow the decoding of conceptual information [1].

[1] investigates the possibility of identifying conceptual representations of EEG related to events based on the presentation of an object in different modalities: its spoken name, its visual representation and its written name. Bayesian logistic regression is implemented with a multivariate Laplace before classification, to identify the neuronal activity related to the concepts from ERP. The highest accuracies (89% of

correctly classified tests) were obtained by classifying the drawings of objects (their visual representation).

In [16], a set of advanced data extraction techniques is presented that allows deciphering the category of individual concepts from individual tests of EEG data.

A comparison between information measures and ERPs revealed a reliable correlation between the N400 amplitude and a surprise word [5]. These findings suggest that different measures of information quantify cognitively different processes and that readers do not use the hierarchical structure of a sentence to generate expectations about the next word.

[19] bases his research on studying the semantic relationship between pairs of nouns of concrete objects such as "horse-sheep", "swing-melon" and how this activity relationship is reflected in the EEG signals. The authors perform an analysis focused on feature extraction algorithms. They train different classifiers to associate a set of signals to a previously learned human response, belonging to two classes: semantically related or not semantically related. Although the previous studies showed an influence of the perception of the object in the tasks related to the action, in [35] it is verified if the representations of the action facilitate the recognition of visual objects.

In [30], twelve different categories are selected as visual stimuli and the subjects were presented in a controlled task and an analysis of different ERP calculations is performed where the user distinguishes whether the stimulus presented is an “objective (category detected) / non-objective” or “objective / rest”, and the results provide useful information about the channels and the part of the signals that are affected by different categories of objects in terms of brain signals. In research [8] it is intended to untangle activities at the node and network level in milliseconds of time scale of perception and decision making. Clear and noisy images of faces and houses are used for the task of categorizing images, and EEG records combined with source reconstruction techniques to study when and how oscillatory activity is organized within the FFA, PPA and DLPFC.

In [31], the dynamics of human vision are studied using a combination of rapid rates of stimulus presentation, electroencephalography and multivariate decoding analysis. The representative structure of a large number of stimuli is obtained, and the emergent abstract categorical organization of this structure is presented. In addition, it is possible to separate the temporal dynamics of perceptual processing from the effects of selecting higher-level objectives.

A particularly relevant component for semantic processing is the N400. Subsequent research has shown that N400 components are generated whenever stimulus events induce semantic or conceptual processing. As such, many researchers have used the N400 component of brain waves as a dependent variable in psycholinguistic experiments. [39] investigates how speech and gesture affect interpretation processes in real time, and addresses the cognitive and neuronal processes that mediate speech-gesture integration.

In [28], the author evaluates the contribution of mid-level characteristics to the decoding of conceptual category using EEG and a new paradigm of rapid periodic decoding. It uses a stimulus set consisting of intact objects of the animated categories (for example, fish) and inanimate (for example, chair) and coded versions of the same objects that they were. However, animation decoding for encoded objects was only possible at the slowest periodic presentation speed.

In [26], the EEG signals together with a multivariate pattern recognition technique were used to investigate the possibility of identifying the conceptual representation based on the presentation of 12 semantic categories of objects (5 examples per category). The attentional facilitation of the constituent characteristics does not spread automatically within an object, but depends on the relevance of the specific task of each characteristic. In [37] a novel experimental design is used, which allows simultaneous electrophysiological measurements of the allocation of attention to two different characteristics (rotation and color) within an object (a square). This was possible by presenting a square that evokes two visual evoked potentials in steady state (SSVEP) for rotation and color changes, respectively. Given the continuous oscillatory nature of the SSVEPs, it was possible to investigate the temporal course of neuronal activity in the early visual cortex of the human brain when the subjects attended one of the two characteristics.

5 Identification of Object Categories from fMRI

It has been a lasting challenge to establish the correspondence between a simple cognitive state (such as the thought of a hammer) and the underlying brain activity. In addition, it is unknown if the correspondence is the same between individuals. A recent approach to study brain function uses machine learning techniques to identify the neuronal pattern of brain activity that underlies several thought processes. Previous studies that used a machine learning approach have been able to identify the cognitive states associated with the visualization of an object category, such as houses [1-8]. The central feature of this approach is its identification of a multivariate pattern of voxels and its characteristic activation levels that collectively identify the neural response to a stimulus.

These machine learning methods have the potential to be particularly useful for discovering how semantic information about objects in the cerebral cortex is represented because they can determine the topographic distribution of activation and distinguish the information content in various parts of the cortex. Multivariate pattern analysis is a technique that allows the decoding of conceptual information, such as the semantic category of an object perceived from neuroimaging data. Impressive results of single-trial classification have been reported in studies that used functional magnetic resonance imaging (fMRI) [1].

[1] focused on identifying the cognitive state associated with the visualization in 4 seconds of an individual line drawing (1 of 10 family objects, 5 tools and 5 houses, such as a hammer or a castle). It is able to identify the category of the object, and for the first time, identify both the individual objects and the category of the object that the participant was seeing, based only on the activation patterns of other participants.

In [9], the neural patterns associated with individual objects as well as with categories of objects were identified using a machine learning algorithm applied to activation distributed throughout the cortex. This study also investigated the degree to

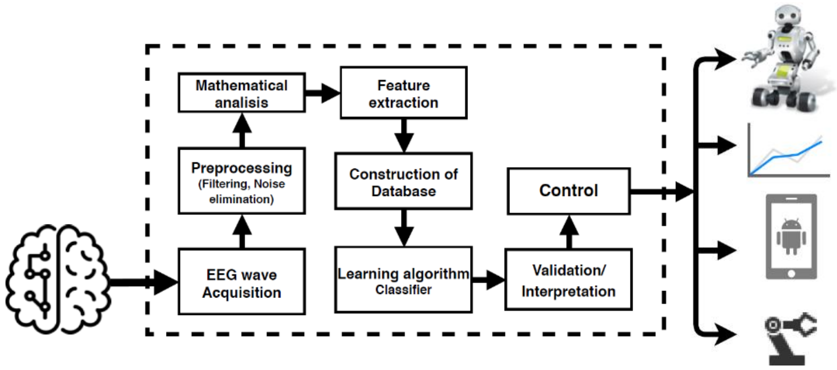

Fig. 2. Methodology required for the analysis of EEG signals oriented to the process of categorization of objects in the human brain.

which objects and categories are similarly represented at the neural level in different people.

[17] trains classifiers to identify which of the ten examples of objects and two categories of objects a participant was seeing.

A common neuronal pattern was discovered among the participants, and was implemented to train a classifier to identify the correct object category and the object example of the fMRI data of new participants who did not participate in the classifier training. In [41] an investigation base on the question of whether it is posible that a coding model based on five semantic attributes directly related to sensory motor experience can successfully predict brain activation patterns caused by word sets. The results show that a lexical concept is not represented identically in different brains, but is a reflection of the unique life of each participant.

In [23], an analysis of lexical categories in the brain is performed, through digital image processing for the detection of regions of the brain that are activated when the user reads abstract and concrete nouns or verbs, in order to classify them into semantic categories. [37] summarizes the evidence of temporal and spatial brain imaging studies that have investigated the emotional effects on the lexical, semantic and morphosyntactic aspects of language during the understanding of individual words and sentences. The revised evidence suggests that emotion is represented in the brain as a set of semantic characteristics in a distributed sensory, motor, language and affective network.

fMRI studies have revealed that DLPFC calculates higher level cognitive functions, including image categorization [8].

Based on the previous analysis, where the research presents its main methodologies, the process that a brain signal requires to be interpreted, and the elements to take into account the process, an approach is made towards the EEG signals and it is proposed that there may be a sufficiently generic methodology for the process of interpretation of the EEG signals oriented to the image classification (Fig. 2).

Tables 1 and 2 present the distribution of the main articles found in the literature that provide distinctive elements of the process of categorization of objects in the human

Table 1. Main methods of analysis, filters and feature extraction processes in the literature for the object categorization process.

	Semantic classification	Method	Filter	Extraction
[17]	Tools and buildings	fMRI	190 s high-passes	PCA
[39]	Animals and tools	EEG	1–30 Hz band-pass filter	
[16]	Mammals and tools	EEG	1–120 Hz band-pass filter to eliminate slow deviations in the signal and high frequency noise, and then sampled at 300 Hz	CSP
[40]	Nouns (sound, color, manipulation, visual movement and Shape)	fMRI		
[23]	Nouns and verbs	fMRI	128 s high-passes	
[19]	Nouns	EEG	Filter passes bands. Finite response filter (FIR) with a lower cutoff frequency of 20 Hz and a high cutoff frequency of 1 Hz.	LPC, PCA, ICA, SEGN FDTW y CSP
[1]	Written words (actions and objects)	fMRI		
[8]	Faces and houses	EEG	Fast Fourier Transformations (FFT), 1-100 Hz band-pass, and a digital noise filter at 60 Hz	
[30]	Animated and inanimate categories	EEG	FIR with Hamming window with 0.1 Hz-100 Hz, and reduced to 250 Hz.	
[27]	Animated vs. inanimate, faces vs. bodies, human bodies vs. non-human bodies, human vs. non-human faces			
[28]	Animated and inanimate images	EGG	FIR with Hamming window 0.1 Hz-100 Hz	
[26]	12 categories of different objects (animals, flowers, body parts, etc.)	EEG	FIR with Hamming window 0.1–150 Hz	

brain, such as the method of analysis of identification of important brain areas, the neural mechanism interpreted, the main component analyzed of the signal, the type of filter applied, the methods of extraction of characteristics, the methods of classification and the categories that classify.

6 Conclusions

The main conceptual advances offered by these findings are that there is an identifiable neuronal pattern associated with the perception and contemplation of individual objects, and that, depending on the type of stimulus, part of this pattern is shared among

Table 2. Main classification methods, brain regions studied, neural mechanisms and components analyzed in the literature for the object categorization process).

	Classification	Region	Neural mechanism	Components analyzed
[17]	Grouped Gaussian-Naive Bayes (GNB) variance classifier	Left hemisphere, ventral premotor cortex and posterior parietal cortex, right parahippocampal gyrus		
[39]		Parieto-occipital central, occipitotemporales	ERP	NI-P2 waves, N400
[16]	SVM		ERP	Ondas NI-P2
[23]		Frontotemporal cortex, inferior occipital cortex, precetral cortex, (IFG)		
[19]	Decision Tree (DT), Naive Bayes (NB), Decision (RL), Artificial Neural Networks (ANN), k-Nearest Neighbors (kNN) and Support Vector Machines.		ERP	P300, N400
[1]		Lateral occipito-temporal cortex, middle temporal area (MT) and medial superior temporal area (MST), left frontal cortex, ventral occipito-temporal cortex		
[8]			ERP	
[30]	LDA with the Representation Similarity Analysis (RSA) framework.			
[27]	SVM with the Representation Similarity Analysis (RSA) framework		ERP	Primary visual area V1 and inferior temporal cortex (IT).
[28]	LDA		ERP	N300, N400
[42]	SVM, regularized least squares with linear and Gaussian cores			
[26]	Naive-Bayesian Classification (NBC)			

various participants. This neural pattern is characterized by an activation distribution across many cortical regions, which involves locations that encode various object properties. The analysis performed gives information about visually represented objects.

The human visual system recognizes objects quickly and the neuronal activity of the human brain generates signals that provide information on the categories of objects seen by the subjects, the results provide useful information about the channels and the part of the signals that are they are affected by different categories of objects in terms of brain signals.

In terms of neural processes of semantics, we have identified scalp locations, time intervals and frequency bands that are especially informative about category differences. The ultimate goal of interaction and cooperation between humans and machines is that a reasonable response be achieved directly to the user's intention.

The technology and brain-computer interface processes are based on direct access to physical activity information in the thinking processes of the human brain, providing an effective neuro-path that allows the interpretation of brain signals. This has become an important development direction in the field of natural language processing.

7 Discussion

Current data shows that the object category can be successfully decoded from the first visual components of the scalp EEG. This contribution is relevant for the investigation of the brain-computer interface. The neuroimaging findings reviewed here provide strong support for models based on sensory-motor properties by revealing a considerable overlap in the neural circuits that support the perception, performance and knowledge of objects. For data analyzes involving fMRI, the high cost of studies may make such systematic explorations impractical.

Fortunately, the studies that demonstrate that conceptual knowledge and semantic category-analysis can be analyzed using EEG, represents a potential research area, in which you can deepen in methods of filtering the acquired signals, in the combination of existing methodologies in order to create hybrid analysis procedures and evaluate their accuracy. Since EEG studies can be performed at a much lower cost than fMRI, they can be a more feasible methodology for large-scale lexical research and categorization.

In contrast, some authors emphasize that EEG techniques involve numerous efforts to improve the accuracy of the location of the neuronal source, and that the information obtained in many of the processes performed is not sufficient to provide a complete and robust estimate of the distribution spatial of the neuronal responses that underlie the perception of different kinds of objects; but that there are specific methods and contributions for this type of signals, in which pattern classification techniques are involved through machine learning.

We believe that large-scale systematic explorations of mental lexicon and categorization with neural data are necessary, which involve both a more careful analysis of conceptual distinctions and a greater range of categories, because most of the papers present comparative analyzes between reduced number of categories, in addition to certain categories are completely isolated from each other.

In this sense, it would be interesting to carry out studies and experiments that allow to know if it is possible to identify concepts through neuronal signals, associated to the process of human communication, that is, to see the possibility of detecting a complete action related to human language.

References

1. Simanova, I., Gerven, M., Oostenveld, R., Hagoort, P.: Identifying object categories from event-related eeg: toward decoding of conceptual representations. PLOS One, pp. 1–12 (2010)
2. Patterson, K., Nestor, P.J., Rogers, T.T.: Where do you know what you know? The representation of semantic knowledge in the human brain. Nat Rev Neuroscience, 8, pp. 976–987 (2007)
3. Mahon, B.Z., Caramazza.: A Concepts and categories: a cognitive neuropsychological perspective. Annual Review Psychology, 60, pp. 27–51 (2009)
4. Gerlach, C.: A review of functional imaging studies on category specificity. J Cogn Neurosci, 19, pp. 296–314 (2007)
5. Martin, A.: The representation of object concepts in the brain. Annual Review Psychology, 58, pp. 25–45 (2007)
6. Binder, J.R., Desai, R.H., Graves, W.W., Conant, L.L.: Where is the semantic system? A critical review and meta-analysis of 120 functional neuroimaging studies. Cereb Cortex 19(12), pp. 2767–2796 (2009)
7. Kanwisher, N., Yovel, G.: The fusiform face area: a cortical region specialized for the perception of faces. Philos Trans R Soc Lond B Biol Sci., 361, 2109–2128 (2006)
8. Chand, G. B., Lamichhane, B., Dhamala, M.: Face or house image perception: beta and gamma bands of oscillations in brain networks carry out decision-making. Brain Connectivity, 6(8), pp. 621–631 (2016)
9. Noppeney, U., Price, C.J., Penny, W.D., Friston, K.J.: Two distinct neural mechanisms for category-selective responses. Cereb Cortex 16, pp. 437–445 (2006)
10. Kozunov, V., Nikolaeva, A., Stroganova, T.: Categorization for faces and tools-two classes of objects shaped by different experience-differs in processing timing, brain areas involved, and repetition effects. Frontiers in Human Neuroscience (2018)
11. Kiefer, M., Sim, E.J., Herrnberger, B., Grothe, J., Hoenig, K.: The sound of concepts: four markers for a link between auditory and conceptual brain systems. The Journal of Neuroscience, 28, pp. 12224–12230 (2008)
12. Hoenig, K., Sim, E.J., Bochev, V., Herrnberger, B., Kiefer, M.: Conceptual flexibility in the human brain: dynamic recruitment of semantic maps from visual, motor, and motion-related areas. Journal of Cognitive Neuroscience, 20, pp. 1799–1814 (2008)
13. Maguire, M., Brier, M., Ferree, T.: EEG theta and alpha responses reveal qualitative differences in processing taxonomic versus thematic semantic relationships. Brain and Language, 114, pp. 16–25 (2010)
14. Sachs, O., Weis, S., Zellagui, N., Huber, W., Zvyagintsev, M., Mathiak, K.: Automatic processing of semantic relations in fMRI: Neural activation during semantic priming of taxonomic and thematic categories. Brain Research, 1218, pp. 194–205 (2008)
15. Martin, A.: The representation of object concepts in the brain. Annual Review of Psychology, 58(1), pp. 25–45 (2007)
16. Murphy, B., Poesio, M., Bovolo, F., Bruzzone, L., Dalponte, M., Lakany, H.: EEG decoding of semantic category reveals distributed representations for single concepts. pp. 12–22 (2011)
17. Shinkareva, S., Mason, R., Malave, V., Wang, W., Mitchell, T. M., Just, M. A.: Using fMRI brain activation to identify cognitive states associated with perception of tools and dwellings. PloS One, 3(1) (2008)
18. Pulvermüller, F.: The neuroscience of language: On brain circuits of words and serial order. Cambridge: Cambridge University Press (2002)
19. Calvo, H., Paredes, J., Figueroa-Nazuno, J.: Measuring Concept Semantic Relatedness through Common Spatial Pattern Feature Extraction on EEG Signals. Cognitive Systems Research (2018)

20. Grill-Spector, K., Malach, R.: The human visual cortex. Annual Review of Neuroscience 27, pp. 649–677 (2004)
21. Kanwisher N, Downing P, Epstein R, Kourtzi Z.: Functional neuroimaging of visual recognition. In: Handbook of Functional NeuroImaging of Cognition, Eds. Cabeza, R., Kingstone, A., pp. 109–152 (2004)
22. Martin A.: Functional neuroimaging of semantic memory. In: Handbook of Functional NeuroImaging of Cognition, Eds. Cabeza, R., Kingstone, A., pp. 153–186 (2001)
23. Chand, G., Lamichhane, B., Dhamala, M.: Face or house image perception: beta and gamma bands of oscillations in brain networks carry out decision-making. Brain Connectivity (2016)
24. Moseley, R., Pulvermüller, F.: Nouns, verbs, objects, actions, and abstractions: Local fMRI activity indexes semantics, not lexical categories. Brain and Language, 132C, pp. 28−42 (2014)
25. Cox, D.D., Savoy R.L.: Functional magnetic resonance imaging (fMRI) ‘‘brain reading’’: detecting and classifying distributed patterns of fMRI activity in human visual cortex. NeuroImage, 19, pp. 261–270 (2003)
26. Spiridon, M., Kanwisher, N.: How distributed is visual category information in human occipito-temporal cortex? An fMRI study. Neuron, 35, pp. 1157–1165 (2002)
27. Behroozi, M., Daliri, M., Shekarchi, B.: EEG phase patterns reflect the representation of semantic categories of objects. Medical & Biological Engineering & Computing (2015)
28. Grootswagers, T., Robinson, A., Shatek, S., Carlson, T.: Untangling featural and conceptual object representations. NeuroImage, 202 (2019)
29. Helbig, H., Graf, M., Kiefer, M.: The role of action representations in visual object recognition. Experimental brain research. Experimentelle Hirnforschung. Expérimentation cérébrale (2006)
30. Mohammad, R., Mitra, T., Kavous, S.: EEG signature of object categorization from event-related potentials. Journal of Medical Signals & Sensors, pp. 37−44 (2012)
31. Grootswagers, T., Robinson, A., Carlson, T.: The representational dynamics of visual objects in rapid serial visual processing streams (2018)
32. Hanson, S.J., Matsuka, T., Haxby J.V.: Combinatorial codes in ventral temporal lobe for object recognition: Haxby revisited: is there a ‘‘face’’ area? NeuroImage 23, pp. 156–166 (2001)
33. Chao L.L, Haxby J.V, Martin A.: Attribute-based neural substrates in temporal cortex for perceiving and knowing about objects. Nature Neuroscience, 2, pp. 913–919 (1999)
34. Bookheimer, S.: Functional MRI of language: new approaches to understanding the cortical organization of semantic processing. Annual Review Neuroscience, 25, pp. 151–188 (2002)
35. Grill-Spector, K., Malach, R.: The human visual cortex. Annual Review Neuroscience, 27, pp. 649–677 (2004)
36. Giraud, A.L., Kell, C., Thierfelder, C., Sterzer, P., Russ MO.: Contributions of sensory input, auditory search and verbal comprehension to cortical activity during speech processing. Cerebral Cortex, 14, pp. 247–255 (2004)
37. Hinojosa, J.A., Moreno, E., Ferré, P.: Affective neurolinguistics: towards a framework for reconciling language and emotion. Language, Cognition and Neuroscience, pp. 1−27 (2019)
38. Schwarzlose, R.F., Baker, C.I., Kanwisher, N.: Separate face and body selectivity on the fusiform gyrus. Journal of Neuroscience, 25(47), pp. 11055–11059 (2005)
39. Grill-Spector, K., Henson, R., Martin, A.: Repetition and the brain: neural models of stimulus-specific effects. Trends Cognitive Science, 10, pp. 14–23 (2006)
40. Wu, Y., Coulson, S.: How iconic gestures enhance communication: An ERP study. Brain and Language, 101, pp. 234−245 (2007)
41. Fernandino, L., Humphries, C.J., Seidenberg, M.S., Gross, W.L., Conant, L.L., Binder, J. R.: Predicting brain activation patterns associated with individual lexical concepts based on five sensory-motor attributes. Neuropsychologia, 76, 17–26 (2015)

42. Isik, L., Meyers, E., Leibo, J., Poggio, T.: The dynamics of invariant object recognition in the human visual system. Journal of neurophysiology (2013)