Neuro-Conceptualization:
Visual Conceptual Modeling meets Neuroscience

John Krogstie and Kshitij Sharma

Norwegian University of Science and Technology, NTNU, Trondheim, Norway

Abstract

A lot of research has been done on the comprehension and development of conceptual models. In other related areas such as linguistics and software engineering one has taken techniques from neuroscience into use, to study the biological and neurological processes when working with textual knowledge representations. This has only to a limited extent been the case when it comes to visual conceptual models so far.

We will in this paper present ongoing research on the use of techniques from neuroscience to investigate how we develop and comprehend visual conceptual models. Traditionally, neuroscience techniques have been depending on EEG or even large MR-machines for techniques such as fMRI, and we outline planned work, also for being able to study modeling tasks closer to how they are actually performed by using multimodal data analysis.

Keywords

Novel directions Talk, Conceptual process modeling, NeuroIS

1. Introduction

NeuroIS is a research field in which neuroscience theories and tools are used to better understand information systems phenomena. Existing research areas in NeuroIS is summarized in [14], where it appears that the main focus is on the use of information systems. Lately also software development tasks such as programming has been heavily studied in literature [12], whereas other tasks often linked to IS-development such as visual conceptual modeling has so far to a very limited degree been studied using techniques from neuroscience beyond the use of eye-tracking techniques [5].

Visual conceptual modeling is a central activity in information systems analysis and design. It involves the construction of abstract models that capture the structure, behavior, and relationships of real-world entities or concepts, and the two-dimensional layout allows to play with both the primary and secondary notation [7] to convey meaning. Integrating neuroscience techniques into conceptual modeling open up new opportunities for understanding how the human brain processes and represents complex information, which can, in turn, inform and enhance the development of more effective modeling approaches when looked upon together with insights form fields such as conceptual modeling, linguistics, and cognitive psychology.

The use of neuroscience in conceptual modeling primarily focuses on understanding the neural mechanisms underlying concept formation, representation, comprehension and manipulation. By leveraging advanced neuroimaging techniques such as functional magnetic resonance imaging (fMRI[2]), functional near-infrared spectroscopy (fNIRS[3]), and electroencephalography (EEG[4]), researchers can

13th International Workshop on Enterprise Modeling and Information Systems Architectures (EMISA) Stockholm, Sweden 2023
EMAIL: john.krogstie@ntnu.no, Kshitij.sharma@ntnu.no
ORCID: 0000-0003-4830-1876; 0000-0003-3364-637X

[2] fMRI: A magnetic resonance imaging (MRI) scanner measures blood oxygenation in the brain and exploits the different magnetic properties of oxygenated and deoxygenated blood.
[3] Functional Near-Infrared Spectroscopy (fNIRS) is a brain imaging technique that (like fMRI) uses hemodynamic responses to indirectly capture neuronal activity. However, compared to fMRI, fNIRS is less expensive and more portable, offering higher ecological validity
[4] Electroencephalograms (EEG) are recordings of the electrical activity of neurons in the brain. Using electrodes placed on the scalp, EEG measures the summation of synchronous postsynaptic action potentials produced by a population of neurons with a very high temporal precision (milliseconds)

examine brain activation patterns and connectivity while participants engage in tasks that require conceptual reasoning or problem-solving. A challenge with some of the more advanced techniques from neuroscience such as fMRI is that the accuracy of results comes at a cost, in particular on the ecological validity of the trial situation and the cost-benefit of the technique used, thus we are aiming for using less intrusive techniques in concert in combination with multimodal data analytics. A comprehension description of current techniques in neuroscience as applied in informatics can be found in [12].

Moreover, the study of individual differences in conceptual processing and the neural basis of expertise in specific domains can provide valuable information on the factors that contribute to the development of expert-level conceptual reasoning and problem-solving abilities.

The use of neuroscience techniques in connection to conceptual modeling has the potential to significantly advance our understanding of the neural basis of complex information comprehension, processing and representation. By combining insights from both fields, researchers can develop more effective conceptual modelling approaches that better align with the inherent capabilities and constraints of the human brain.

As mentioned, techniques such as eye-tracking is used quite a bit for model comprehension and modeling process analysis [1], but papers in the area primarily mention a more extensive treatment with neuroscience techniques to be tried as the next step [15], although other techniques are gradually being taken into use [13]. In this novel direction talk, we will present preliminary plans for experiments on how to use input from a number of different sensors to do multimodal data analysis for proving better understanding on how the brain is doing different modeling tasks.

2. Current research plan

We plan a number of experiments, starting with studying simple model comprehension tasks, being extended to more complex tasks in a setting as close to a normal modeling situation as sensors improves. A normal modeling situation will compared to laying still in an MR-machine involve movement that typically introduce noise which it is hard to deal with in with some of the current sensors, but we see this has improved over the last years and is expected to be further improved. As a start we envisage the following experiments: (partly with inspiration from what that is recently done in the field of code comprehension):

1. Investigate the usage of the brain when working with conceptual/visual models:

RQ 1: Which brain regions are activated during model comprehension (similar to what is done in [9], where one looked at the brain regions active when performing computer program comprehension tasks). Experimental task: a model (in a modeling language known to the participant) is presented to the user, which is to use this for answering presented comprehension questions. Will start with a model in one diagram (i.e., the whole model is visible, no need for scrolling/navigating in a hierarchy etc. to avoid to much bodily movement by the participant. The models to use are similar to those used in standard process model comprehension tasks [6].

2. Investigate the usage of the brain when working with conceptual/visual models as compared to how it operates when using a text expressing the same information (with possibly some parallel to what is done in [2] where differences in working with visual and textual programming languages were investigated)

Main hypothesis: Different parts of the brain is used more intensively when working with visual knowledge representation than when working with textual knowledge representations. Experimental task: Have two domains, both presented as a model and a text, and comprehension questions for both domains. Have a Latin-square set-up to give participants different settings, e.g., one group first see a model of domain A, and then a text of domain B etc. In addition to study the parts of the brain used, measure cognitive load and possibly also other characteristics (see below).

3: Investigate the usage of the brain when using different modeling languages (BPMN vs. UML AD for process modeling for instance). Have a similar latin-square set-up based on models in both languages representing two different domains.

4. How do layout and other aspects of secondary notation influence model comprehension (cf. [9], where they looked at how layout and beacons in source code influence program comprehension). Need to be detailed based on issues found in cognitive psychology, listed as empirical model quality issue in the SEQUAL framework on model quality [4].

5. How can detected information on e.g., cognitive load be used to provide feedback tools to support the modeler.

A more detailed set-up currently done in connection to the first two tasks also extending into affective and behavioral aspects are presented below:

RQ1: What are the differences in affective, behavioral and cognitive processes across different levels of model comprehension?

- Sub-RQ: what are the major brain regions responsible for visual model comprehension?
- Sub-RQ: how does the cognitive load evolve during the comprehension process?
- Sub-RQ: what are the roles of stress and physiological arousal leading to certain comprehension performance level?

Prediction question: how accurately can we predict the comprehension level of the modelers using the affective, behavioral, and cognitive measurements using deep learning networks? What are the various dimensions of explainability in such a predictive model?

The experiment follows a time series repeated measure design as follows, with:

Model 1 → Comprehension statement → NASA-TLX → Model 2 → Comprehension statement → NASA-TLX → ...

Where the models are represented both in text and as visual business process models, and the participants are divided in a Latin-Square fashion. NASA TLX is a self-assessment of task load [11]. We aim to have around 60-70 participants in total. Participants will be recruited from NTNU student and employee population. NTNU has more than 40000 students across all academic fields. The way the study is to take care of protecting the participants privacy has been reported to and accepted by the national authorities in this matter (NSD-approval).

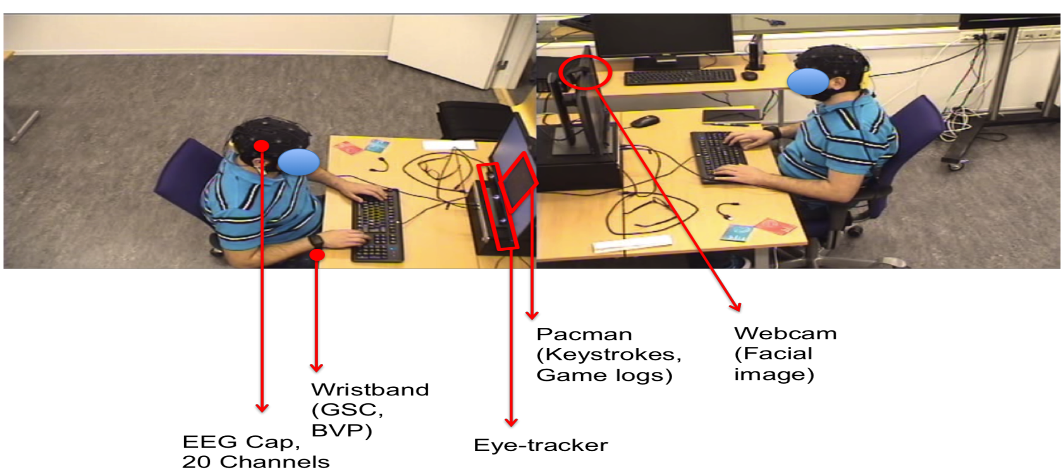

Figure 1: Test setup

Figure 1 illustrates the set-up and the different sensors in the multimodal experimental setup. The setup can provide a large variety of the information about the situation, not all necessary for the specific task, which will be listed below, and also support a richer level of man-machine interactivity than e.g., the use of fMRI and other techniques dependent on more heavy machinery (e.g. MR-machines) pursued in contemporary neuroscience.

2.1. EEG Measurements

- Lower Alpha wave power (8—9 Hz): Relaxed, but not drowsy
- Upper Alpha wave power (10—12 Hz): Normal, relaxed yet focused
- Lower Beta wave power (13—17 Hz): Normal, relaxed yet focused
- Upper Beta wave power (18—30 Hz): Active thinking, alertness
- Gamma wave power (more than 30 Hz): Higher mental activity
- Theta wave power (4—7 Hz): Idling, inefficiency, related to ADHD
- Fractal dimensions: Long term memory
- Bursts in alpha wave: Performance
- Alpha magnitude: Workload
- Decreasing Alpha and Theta band power: Cognitive load
- Phase coupling of Theta and Gamma: Short term memory
- Alpha band power: Attention
- Wavelet coefficients of Gamma band: Emotional intensity
- Theta band power: Memory load
- Increasing theta and decreasing alpha: Increasing performance
- Gamma-band activity: Short term memory load
- Decreasing Theta and Increasing Alpha Working memory

2.2. Eye Tracking Measurements

- AOI[5] hit: How much attention is paid to the different parts of the visual field.
- AOI transition: Attention shift proportions.
- AOI revisit on the screen: Failure of memory/Need for confirmation.
- Local or global saccades (threshold on the saccade length): Focal[6] or ambient[7] cognitive processing.
- Short fixations on a specific part: Anticipation of finding information.
- Number of saccades per unit time: Decreasing task difficulty/ Increasing mental workload/ Increasing arousal.
- Number of blinks per second: Time on task, mental workload, fatigue.
- Blink duration: Drowsiness, mental workload.
- Number of fixations per second Decreasing search efficiency/Expertise based on the task / Difficulty in interpretation.
- Fixation duration: Attention.
- Skewness of fixation duration histogram: Cognitive processing.
- Pupil diameter: Increased emotions, anticipation mental workload/ Decreased drowsiness, fatigue.
- Saccadic velocity: High cognitive load, task difficulty, memory load.
- Scanpath Velocity = number of forward saccades/number of backward saccades: Amount of information processing.

[5] AOI = Areas of interest that are defined by the researcher
[6] Focal: short saccades and long fixations
[7] Ambient = long saccades and short fixations

- Saccade duration: Task difficulty/ Decrease in information processing.
- Saccade velocity: Low arousal and sleepiness
- Saccade velocity skewness: Anticipation
- Cross-recurrence (probability of looking at the same place at the same time): Increases during dialogue episodes also increase during certain dialogue types and verbal and deictic references. Correlates with collaboration quality and outcome.
- Scanpath shape similarity (Overall shape, Same shape but different scale, Similar subparts): Collaborative outcome.
- Gaze similarity: Similar to cross recurrence but temporal measurement.
- Mean and SD pupil diameter; number of long fixations; saccade length: Cognitive load.

2.3. Wristband Measures

Wristband measures are mostly used in prediction, so we lack the measures that are directly interpreted: HR = heart rate, EDA = electrodermal activation (skin conductance), BVP = blood volume pressure, TEMP = skin temperature

- EDA peak height / EDA peak rate / EDA slope: Cognitive load.
- BVP power spectrum low/high ratio / BVP amplitude / # EDA responses detected/ EDA mean/ EDA rising time / TEMP slope: Stress.
- TEMP (mean, sd, kurtosis, skewness)/ EDA peaks / HR variability (mean, sd, kurtosis, skewness): Emotional stress.
- EDA change detection measures: Acute stress cycle (normal, aroused, stressed, relaxed).
- HR recovery rate changes (duration and counts): Chronic stress.

We can additionally compute the action units (AUs) from the faces of the participants capture using cameras. Once we have these AUs then we can compute various emotions as the combination of these AUs, such as Happiness, Sadness, Surprise, Fear, Anger, Disgust, and Contempt. Second, we can compute the emotional profile (entropy of AUs, stability of emotions, emotional similarity between the peers) of the participants similar to [12]. We have not space here to go in detail on the machine learning interpretation of data, but this will be presented at the conference. We also note that using a large number of inputs in parallel brings additional challenges in synchronizing the output of the different sensors.

3. Concluding remarks

Whereas neuro-science techniques are being used for a number of tasks connected to IS usage and programming, the application in connection to the use of visual conceptual models has so far been limited. We have in this novel direction talk given an overview of a multi-modal approach for capturing neuro-scientific data in connection to conceptual modeling, which we hope will bring up ideas in the conference for how to bring this area of research forward.

4. References

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