UCHRON

An Event-Based Generative Design Software Implementing Fast Discriminative Cognitive Responses from Visual ERP BCI

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This research aims at investigating BCI technologies in the broad scope of CAAD applications exploiting early visual cognition in computational design. More precisely, this paper will describe the investigation of key BCI and ML components for the implementation and development of a software supporting this research: Uchron. It will be organised as follows. Firstly, it will introduce the pursued interest and contribution that visual-ERP EEG based BCI application for Generative Design may provide through a synthetic review of precedents and BCI technology. Secondly, selected BCI components will be described and a methodology will be presented to provide an appropriate framework for a CAAD software approach. This section main focus is on the processing component of the BCI. It distinguishes two key aspects of discrimination and generation in its design and proposes a new model based on GAN for modulated adversarial design. Emphasis will be made on the explicit use of inference loops integrating fast human cognitive responses and its individual capitalisation through time in order to reflect towards the generation of design and architectural features.

Keywords: Human Computer Interaction, Neurodesign, Generative Design, Design Computing and Cognition, Machine Learning

INTRODUCTION

Overview
One can see today how deeply linked are the developments of artificial with natural aspects of intelligence in encoding the world and developing models of understanding it. A classical separation between both forms of intelligence is only highlighted here as a foreword to introduce the complementary use of Machine Learning (ML) models together with human cognition in the hereafter described research.

Looking within the research and development fields of Brain-Computer Interfaces (BCI), implemented ML models from data acquisition to classification tasks in general are a great example of complementary loops of inference together in response with the neuro-feedback of a user for re-capacitation of motor or other cognitive skills in medical applications such as neuro-prosthetics for example. But aside medical research and among the abundant literature and initiatives to bring BCI Out-Of-The-Lab (OOTL) and to
other disciplines for research and application purposes, it has been quite rare to find architectural or design research contributing in investigating or re-purposing such technologies, despite their accessibility. Yet potentials and consequences in Computer-Aided Architectural Design (CAAD) should be at least of the same level than for construction technologies, material engineering or even environmental data-science; once considered for a broaden understanding, reachability and impact on the world in which one operates. This research aims at investigating such technologies in the broad scope of CAAD applications. More precisely, this paper will describe the investigation of key BCI and ML components for the implementation and development of a software supporting this research.

**Precedents**

While establishing a prior background for applicative potentials, and experiments, suggestions have been made on the specificities of acquiring, treating and integrating peculiar neurosignals for iterative shape generation and selection systems (Cutellic and Lotte 2013; Cutellic 2014). In addition to a broaden understanding of the technologies involved in BCI and in-depth experiments of their applications, these precedents opened a ground for reactivating architectural research in the context of Human-Machine Interaction (HMI) and neural phenomena. Recent works have shown practical models in which the development of mixed intelligence models for encoding shape features offers further potentials in CAAD by considering vision as inverse graphics. This paper will now focus on describing a synthetic approach in the form of a software called Uchron, integrating BCI technologies and previous work to support further research in these directions.

**a Visual-ERP, EEG-Based BCI**

A general definition of a BCI involves the digitisation of neural activity transduced into signals, acquired from the Central Nervous System (CNS, or brain), and then translated to messages or commands for an interactive application, once such signals have been first measured and processed into classifiable patterns. As an interface, it may then constitute a feedback loop of inference between a human and a machine (see fig 1). For applicative reasons, the present research focuses on online (data acquisition, classification and stimulation happening successively in loop), synchronous (stimuli and acquired data synced in the same time segment), and non-invasive technologies (more precisely Electroencephalography - EEG - to measure residual electrical signals at the surface of the scalp) (Farewell et al. 1988). This choice is justified by giving priority to the development of a visual generative design model in correlation with neurosignals and focusing on the software development while setting minimal requirements for acquisition hardware (see section Acquisition and pre-processing). As there are many signals measured by EEG, this research makes extensive use of visually-evoked potentials represented in the time domain (t-VEP). This choice is justified by the current necessity to correlate visual events, or stimuli, with neural patterns in time. Nonetheless, frequency (f-VEP) and code modulated (c-VEP) potentials are also worth mentioning for future perspectives (Bin et al. 2009). A specific subtype of standard and robust evoked potentials working in the visual field are used throughout the entire research and are called endogenous Event-Related Potentials (ERP). They are resulting from specific events or stimuli, and detected from a few hundred milliseconds onset stimulus, while reflecting cognitive tasks of higher-order invoked in relation to working memory, expectation, attention, or changes in the mental state (Luck 2014). Currently, ERP are one of the most widely used methods in cognitive neuroscience research to study the physiological correlates of sensory, perceptual and cognitive activity associated with information processing (Luck 2012). One of the major ERP component of interest for this research is the p300 wave (or p3), often used as metrics of cognitive functions in decision making processes, as its two components (p3a and p3b), are mostly correlated with the processing of novelty and improb-
able events (Polich 2007). Since its discovery (Sutton et al. 1965) as a large positive wave occurring approximately between 250ms and 700ms onset stimulus, the p300 has become a popular signal to integrate in BCI, once combined with elicitation paradigms (see section From Static To Generative RSVP Elicitation Paradigms).

**Figure 1**
A typical ERP BCI involving a visual RSVP elicitation paradigm and presenting its three main components: data acquisition, signal processing and stimuli feedback. All three main components may be greatly vary. Stimuli may be single or multi-sensory (visual, auditory,...), Acquisition may be multi-modal (EEG, EOG, ...), and Processing may vary greatly in the vast range of ML models depending on the classification or regression task at work for the even signals.

**METHODS AND BCI COMPONENTS**

This section main focus is on the processing component of the BCI. It distinguishes ML use and developments for two different purposes in the framework of BCI implemented in GD. One has a discriminative purpose, and another one a generative purpose. Both are used in a complementary way to fill a loop of inference. Discrimination is essential in the classification of neural patterns (section From Static To Adaptive Classification Algorithms As Discriminative Models), while generation is a primordial component in the production of novel and/or modulated visual feedbacks (section From Generative Design to Modulated Generative Adversarial Design). Their complementarity in regards to advancements in ML are an important aspect of this implementation. The elicitation paradigms structuring the generative module will also be presented (section From Static To Generative RSVP Elicitation Paradigms). Section “Acquisition and pre-processing” provides minimal standards for acquisition and pre-processing in this framework.

**Acquisition and pre-processing**

Primary goals being to transpose existing and effective non-invasive BCI paradigms to users with healthy brains (independent from pathology diagnosis), allowing for single trials and field recordings (signal processing improvement through post-treatment, mobile and hybrid BCI), additional criterias are added and complementary with the software development part: portability (needs to be wireless and have an internal powering system), versatility (dry sensors, lightweight device, reconfigurable acquisition) and deployability (open acquisition firmware and data formats, platform and device agnostic). These criteria are not mandatory for the development of the present software but constitutes consequently minimum requirements which would only improve with any hardware upgrade. A review for some of these compliant devices may be found there (Debener et al. 2012, Duvinage et al. 2013, Frey 2016, Ramadan et al. 2017). As non-invasive EEG techniques and neurosignals in general are already noisy, we are working at a minimum with 16 electrodes, or channels, positioned on the International 10-20 referencing system. As an example, electrodes may be positioned with the following references: FCz, FC3, FC4, Cz, C3, C4, T7, T8, Pz, P3, P4, P7, P8, Oz, O1, O2. Signals are digitised at a minimum of 125Hz. Among the various ways to represent EEG signals, this research mainly uses data points in the time domain, concatenated from all acquisition channels and typically used in p300-based BCIs. Data is then filtered with a 8-order Bandpass filter with low and high cut-off frequencies of 0.1 Hz and 20 Hz in order to avoid DC drifts and main artifacts if the hardware amplifier does not ensure it. After a time segmentation of 0.700 ms or below onset visual stimulus, each signal is downsampled to 20 Hz. This allows both for reducing the amount of datapoints and the speed of processing while maintaining a visual feedback loop. Lastly, the data is normalised to zero mean and unit variance for better generalisation from the classifier. No further feature extraction is performed to maintain minimal processing time in an online BCI setup and try to directly
learn from data as raw as possible. Future developments will maintain this criteria.

**From Static To Adaptive Classification Algorithms As Discriminative Models**

There have been a vast amount of classification algorithms applied to BCIs along with the developments of ML (Lotte et al. 2007, 2018). While a current version of the developed software relies already on applied robust static models (Cutellic and Lotte 2013; Cutellic 2014) lastly using a voting ensemble method of linear Support Vector Machines, ie. SVM (Rakotomamonjy et al. 2005), this paper also describes ongoing adaptations to referred state-of-the-art dynamic classifiers. While SVM remain popular classifiers for BCIs using EEG signals, a newer generation of dynamic classifiers has emerged to answer more effectively specific challenges - namely noisy signals, small training samples, non-stationarity and high dimensionality of data - still unreachable by, otherwise successful, deep learning models to this date. In addition, the currently implemented model of I-SVMs Ensemble has established clear base criteria to elaborate from and among which the computational simplicity with zero hyperparameters optimisation, general robustness and speed of execution play important roles in the trade-off. For these points, adaptive Riemannian Geometry Classifiers appear to be the best candidates so far for a steady development (Congedo et al. 2017, Yger et al. 2017), and currently the Riemannian Minimum Distance to Mean classifier (RMDM) in the scope of P300 BCI (Barachant et al. 2014). Future developments will not consider co-adaptive training in the choice of classification algorithms as they directly concern issues of control over time (Vidaurre et al. 2011). However, Transductive Transfer Learning (Pan et al. 2010, Courty et al. 2015) is considered to be an important point of future developments in order to transfer trained models from one domain to another (from one user to another or from one session to another) and in combination with aforementioned adaptive classifiers (Lu et al. 2009). Since it is already considered as an important aspect of research towards a calibration-free BCI (Congedo 2013) and may reveal creative potentials by transposing user and/or session models.

**From Static To Generative RSVP Elicitation Paradigms**

The Rapid Serial Visual Presentation (RSVP) paradigm is part of a much vaster range of elicitation paradigms and commonly used in neuroscience for its locked-in temporal characteristics to address, jointly or separately, studies in perception and cognition in relation to visual attention. It consists in displaying sequentially static visual stimuli (images), or moving ones (videos) at the same spatial location and at a high frequency rate of multiple stimuli per second. The physiological response is then measured in a temporal window onset stimuli and under the assumption that some of the stimuli within the serial presentation will elicit a response (Spence et al. 2013). Although psychological elicitation paradigms were first introduced into the neuroscientific study of ERP before becoming a generalised technique for event-related cognitive responses (Squires et al. 1975, Donchin 1981), it later became a common neuropsychological technique due to the short latency and high temporal resolution of event-stimuli correlation such combination can provide (Rugg et al. 2008). There exist a limited set of well studied paradigms in correlation with known ERP but which allows for a wide range of inferences on cognitive processes such as inattentive auditory processing, selective attention, stimulus evaluation, working memory updating, movement preparation and inhibition, error processing memory, language processing, face processing, or even mental chronometry (Kutas et al. 2012). This research focuses on a well studied paradigm used to elicit a p300 wave and based on the principle of discrimination: the oddball paradigm (OP). The OP is a typical RSVP task with frequent, random, deviant stimuli: an oddball (Kutas et al. 2012). These peculiar stimuli are then used to detect the elicitation of an ERP. In the case of a visual OP, a series of self-similar events are shown at fast pace in sequences of a few
milliseconds (see Figure 2). The current RSVP strategy makes extensive use of the temporal structure of the OP paradigm in order to correlate both signals and stimulus in time for a later processing and derives the first implementations from an existing and stable model on visual ERP and widely used for BCI research competitions and benchmarks: the p300 speller (Donchin et al. 1988, 2000). In the case of spelling or more generally in ERP BCIs, stimuli are static items (ie. fixed characters to spell words or stable images to classify them). In the case of design and architecture research, the capacity to generate and/or modulate the stimuli within a similar temporal structure is of high interest and achievable (Cutellic and Lotte 2013, Cutellic 2014).

**Figure 2**
Figure 2. A typical visual oddball paradigm in a RSVP task to elicit ERP. Each stimulus presentation epochs, and in-between epochs consist of a few milliseconds in the time domain and in the elicitation range of the studied ERP wave.

**From Generative Design to Modulated Generative Adversarial Design**
A most general definition of generative design (GD) can be applied from generative art (Galanter 2003) as the use of linguistic or procedural rules in a relatively autonomous system to generate, in an iterative fashion, novel design solutions and increase their variance. In a similar way, a generative algorithm in ML can be seen as learning, in an unsupervised way, the probability of features and implicit patterns from data (Ng et al. 2001). They can, in return, generate a vast amount of outputs with similar features and in large variance. A recent approach to improve the quality of this model is through an adversarial method together with a discriminative algorithm, or GAN (Goodfellow et al. 2014, Salimans et al. 2016). In such method, both generator and discriminator are trying to minimise their loss function. The discriminator is trying to classify outputs by their contextual relevance (ie. an object class) and the generator is adapting its parameters in order to pass discrimination, similar to an actor-critic strategy used in reinforcement learning (Pfau et al. 2016). Two major interests are pursued in this research in regards to contributing to GD. Firstly, is to evolve GD preconditions from a set of rules to unstructured ensembles of data. In that aspect, GANs and other generative models are of high interest. Secondly, the clear separation of GAN models between a generator and a discriminator makes it an appropriate candidate to integrate in a BCI framework. While the generator purposes on updating visual output for RSVP, the discriminator can be adapted with previously described discriminative models for EEG neural patterns (see section 2.2). In such feedback loop, the discrimination is modulated by the decoded neural pattern, may offer visual object categorisation of higher complexity, while generating visual features as a user experiences it. This research assumption spans beyond the scope of this paper which purpose is to describe a software implementation to support its development in real time interface for GD. Additionally, a third interest of using GAN is also in the generation of training data in a more conventional model to accelerate implementations of experiments. As previously mentioned in section 2.2, and in a previous paper an initial implementation using simple rule-based GD models together with an ensemble of SVM was used to assess criteria and potentials to evolve towards the modulated generative adversarial design model in current development.

**Implementation**
This section will focus on the general framework and its main aspects. Further details and UX flows will be added together with the future developments aforementioned. During precedents, we opted for the OpenVibe software (Renard et al. 2010) and developed further work from provided algorithms such as xDawn (Rivet et al. 2009, Cutellic and Lotte 2013). Due to the rapid development of Information Technologies and the before-mentioned requirements of
this research, we maintained preferences for open-source and platform-agnostic solutions. The first orientation was made towards Python-based technologies related to cognitive science applications. Its rapid evolution for the related scientific and industrial disciplines (Muller et al., 2015) made it a choice of first order and easy to combine to other CAD packages and APIs. It is worth mentioning similar initiative as a reference on feedbacks framework (Venthur et al. 2010), signal acquisition (Venthur et al. 2012) and signal processing (Venthur et al. 2015). Yet, online processing and up-to-date coding (Python 3+) were needing further work and added-up to the list of necessary developments for a fully functional ERP feedback loop as a web-based application and including user databases and encrypted data, open acquisition streams and formats, classification, plugins and visual experiments catalogs (see fig 3). We are currently actively pursuing this part, using python Django web frameworks. This allows for a modular and scalable approach which can be maintained both in a research and application framework while updating separate technological modules. Additionally, this renders the acquisition of data and its processing distributed. Most of the computational is done by the middleware on the server and therefore can maintain a lightweight front-end which is device agnostic for the acquisition and os agnostic for the visual feedbacks. The visual feedback module consists on recent html5 and webgl rendering standards. Communication protocols are ensured via web sockets and django channel layers. The middleware is both connected to a backend user database (storing user settings and data) and the front end to get data both from acquisition devices and the feedback module. The data gathered is sent first to the pre-processing module and then to the discriminator/generator module. A modulated feedback is sent back to the feedback module with the possibility to stream external outputs in numerous formats for this
party software (LSL, OSC, UDP,...). Prior to acquire data, after pre-processing and after training the discriminator, requests are sent to the Backend to get user based specific settings for acquisition and optional streaming. The pre-processed data and trained classifiers are stored and can be retrieved or downloaded by the user over sessions.

CONCLUSION AND FUTURE WORKS
This paper has described the general and first implementation of Uchron, a software based on visual ERP EEG-based BCI for Generative Design. After identifying key technologies and state-of-the-art components of its current state and future development, it has introduced a new ML model based on GAN for Modulated Generative Adversarial Design and involving both ML and Human Cognitive features. Future work on the software will now focus on the development of such model.

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