A Translational Approach to Neurotechnology Development

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Abstract. The past several decades have seen an explosion of meaningful and nuanced insights into the connection between human behavior and the nervous system; however, the translation of these insights into viable applications is a non-trivial and widely acknowledged challenge. Recent advancements in brain-computer interaction and real-world neuroimaging technologies have provided major breakthroughs that provide the underpinnings for translational neuroscience research efforts. This session focuses on building off of those advancements and specifically proposes three concepts necessary for overcoming the challenges of translation: 1) integrating aspects of knowledge of brain function that are generally separate into single analyses, 2) increasing situational complexity, and 3) continuing to develop neuroimaging tools specifically for use in real-world environments.

Keywords: Translational Neuroscience, Neurotechnology, Brain-Computer Interface (BCI), Electroencephalography (EEG), Neural Classification.

1 Introduction

The past several decades have seen an explosion of meaningful and nuanced insights into the connection between human behavior and the nervous system; a connection that is considered to be foundational for understanding how we perceive and interact with the external world. Underlying the discovery of these insights is the highly active field of neuroscience, which has generated approximately $\frac{1}{2}$ million citable documents over the past 15 years [1]. Analysis and recommendations from numerous sources including the Office of the U.S. President and the National Research Council suggest that the continued advancements in neuroscience have the potential to revolutionize human-system integration technologies and have a dramatic impact on society at large [2–4]. However, translating basic neuroscience research into viable applications is a non-trivial and widely acknowledged challenge, particularly within the medical community [5].

The difficulties in translation are due, in large part, to the overwhelming complexity of the human brain and its approximately 100 billion neurons. Most basic neuroscience research has been largely conducted using a reductionist approach in which experimental

variables are highly controlled and both stimuli and behavioral responses are relatively simple compared to those found in real-world settings. These highly constrained laboratory environments are often used to enhance signal-to-noise ratios, and limit the behaviors and interactions study participants normally have with the world. Although this research has advanced our basic understanding of brain function within highly constrained environments, the extent to which controlled laboratory research results generalize to brain function in complex and dynamic real-world environments is currently not well understood [6, 7]. Further, it has been argued that the complexity of the human brain allows not only different individuals to process information differently, but also the same individuals may engage different brain structures to cognitively process similar information, particularly in response to contextual changes [8]. These concepts suggest that there may be fundamental differences in real-world brain function relative to that observed in highly controlled laboratory environments, thus supporting the need for more ecological approaches [9] focusing on human, task, and environmental interactions [10] within real-world environments. We posit that such approaches would lead to a more representative understanding of real-world brain function and enhance the success of translational neuroscience efforts.

2 Translational Advances in Human-System Integration

The potential for translating neuroscience into revolutionary human-system integration technologies has been recently boosted by technological advancements in two areas: the rise of brain-computer interaction (BCI) technologies and the advent of real-world neuroimaging tools. These advancements have enhanced not only the ability to measure neural activity in real-world situations, but also the ability to interpret neural data generated within complex scenarios. As discussed below, the technologies and insights generated in these two fields are now enabling the ecological approaches needed for successful translational neuroscience.

The past decade had seen a surge of research and technological advancements in BCI and associated technologies, particularly as applied to the medical domain. Many of the advancements in BCI arose from the unique combinations of researchers focused on the man-machine problem as opposed to simply addressing the traditional neuroscience questions underlying nervous system function. Early BCI efforts focused on providing communications and direct control capabilities to specific clinical populations [11]. However, the mix of scientific and engineering approaches have changed the focus of the original BCI efforts (e.g., for discussion, see [12]), and provided novel insights into not only how neuroimaging could be effectively integrated in system designs, but also how the brain functions. These understandings are allowing researchers to uncover approaches to integrate emotion into video games, toys, advertising, and music [13, 14], merge human pattern recognition with computer processing power for joint human-computer object detection [15, 16], and overall, develop applications that use neural signals in ways that are more consistent with the brain function that naturally occurs during task performance [17]. Importantly, the efforts in this domain have augmented current methodologies and given rise to a wide variety of novel research approaches and tools for analyzing and interpreting neural

signals in complex settings. For example, the BCI community has made dramatic improvement in real-time signal processing and the use of machine learning approaches including artificial neural networks and signal classification methods for neuroimaging.

Driven by a focus on application, recent advances in BCI technologies have provided proof-of-principle that neurotechnology applications can be effective outside clinical and controlled laboratory settings; however, the state-of-the-art in this area is still limited in its utility. For example, direct control BCIs are becoming viable for clinical populations; but, their performance is still well below that of healthy users employing traditional optimized control devices such as a keyboard, mouse, or joystick. In the near future, we expect greater translation into the BCI field as the focus of BCI's shift towards use by healthy populations. We foresee three technical areas aiding the translational effort: more effective approaches to integrating neural processing into BCI design, the integration of BCIs into more complex situations, and a shifting focus to BCIs that accomplish unique tasks that are difficult to accomplish through other means (for examples, see [4, 18]).

The second major advancement over the past decade has been the development of neuroimaging tools for use in operationally relevant settings, which has been enabled in large part due to DoD programs such as Augmented Cognition [19]. Neural sensing technology is one area that has seen several significant advancements in recent years (for a full review, see [20]). Specifically, electroencephalography (EEG) has shown the most promise as a near-term solution to the challenges of quality, mobility and wearability within realistic operational environments. Recent advancements occurring in the areas of dry, comfortable EEG electrodes and wireless EEG systems have shown particular promise. A second area of advancement has been in EEG analytic techniques and approaches (for review, see [21]) and accessible software for both off-line and real-time EEG analysis. These tools are enabling steady progress toward real-world neuroimaging capabilities. Significant conceptual progress in both hardware and software still needs to be accomplished to enable end state goals of wear-and-forget sensing technologies capable of producing laboratory grade results in real-time and in environmental conditions never before deemed possible.

3 Three Translational Concepts for Human-System Integration

In this session, we highlight three concepts that build off of the advancements in BCI and real-world neuroimaging technologies to enable the translation of neuroscience needed to provide revolutionary advances in military neurotechnologies projected by the National Research Council and others (e.g., [3]). The first three talks of the session focus on improving signal analysis, classification, and interpretation through a integrating a better understanding of nervous system function into classifier design. In the fourth talk, the speaker will focus on the translation of a BCI into operationally complex situation. The final talks of the session will focus on tools for improving real-world neuroimaging and neurotechnologies.

3.1 Integrating Multiple Aspects of Neuroscience Knowledge into Single Analyses

The vast extant neuroscience literature is filled with important and interesting insights into brain function. However, many of the neuroscience studies and applications to date focus on isolated research areas, avoiding potential confounds or contextual modulations that make interpretation difficult. For example, much of the direct control BCI literature avoids the psychological construct of mental fatigue by designing studies that are limited in duration or by throwing out data when subjects seem fatigued. In the first part of this session, we focus on attempting to merge different conceptualizations of nervous system function into single analyses to overcome some of the aforementioned confounds or contextual modulations that make interpretation difficult. Specifically, in the first three talks, the speakers focus on combining known but underutilized information about brain function into more traditional analyses for improved performance:

- Amar Marathe and colleagues examine the classification of targets from neural data as participants perform a rapid, serial visual presentation (RSVP) task [22]. According to the literature, during complex situations, temporal variability exists between stimulus presentation and the measurement of neural responses due to factors both internal and external to the operator. However, to date, target classifier schemes have not effectively accounted for this trial-by-trial variability. Dr. Marathe presents a study that describes a novel classification method that accounts for temporal variability in the neural response to increase classification performance and behavioral prediction. Specifically, using sliding windows in hierarchical discriminant component analysis (HDCA), they demonstrate a decrease in classification error by over 50% when compared to a state-of-the-art HDCA method.
- Jon Touryan and colleagues examine the generalizability of fatigue-based measures of EEG to predict task performance [23]. As previously mentioned, BCI research has often avoided addressing fatigue.. Dr. Touryan presents a study that takes the first steps towards developing an RSVP-based BCI that continues to effectively function as operators become fatigued. He presents a study that extends the fatigue-based performance prediction algorithms developed for the driving domain [24] to RSVP performance prediction and demonstrate similar results for both tasks. This study illustrates the capability to detect the state-based information stream within an existing BCI task (i.e., RSVP) that is needed to extend BCI algorithms that adapt to user state.
- Greg Apker and colleagues examine the ability to use fatigue-based measures of EEG to predict driving performance [25]. Previous research has shown the ability to make such predictions based on findings of a linear relationships between power spectral density estimates of EEG and driving performance in simple driving tasks [24] However, the extant literature also suggests that this simple relationship is insufficient based on multiple findings including: 1) task performance depends on numerous factors in addition to fatigue and 2) state changes in the brain may produce non-linearities in the relationship between the EEG signal and behavior.

Dr. Apker presents a study that merges a quadratic discriminate classifier with a modified version of the original linear approach and demonstrates prediction improvements through the inclusion of the non-linear element.

3.2 Increasing Situational Complexity

Theoretical and experimental evidence suggests that there are fundamental differences in how the human brain functions to control behavior when it is situated in ecologically-valid environments (i.e., situated cognition) versus that observed in highly-controlled laboratory environments. We hypothesize that a portion of our understanding of brain function will generalize to real-world settings, and from a translational perspective, it is critical to identify which portion. This generalizability issue defines the need to expand the capability of neuroimaging technologies beyond the laboratory and into complex situations where natural human, task, and environmental interactions can be studied. The fourth talk of the session illustrates the successful translation of a generalizable research finding to a complex scenario:

- Anthony Ries presents data supporting the use of the RSVP task for searching imulated urban environments with performance improvements over a manual search of the same environment. Second, Dr. Ries presents the development underlying a novel simulation environment designed to aid the translation of the RSVP into a more realistic context. Specifically, the novel simulation environment embeds the RSVP into an operationally-relevant multitasking scenario where the operator is required to search for targets, identify IEDs near the roadside, and respond to specific radio communications while riding in a simulated moving vehicle. The initial results of a validation study support the successful translation of the RSVP task into the more complex environment with the neural-driven target detection approach outperforming manual target detection [26].

3.3 Developing Neuroimaging Tools Specifically for the Real-World

The capability to extend both science and applications into a wider variety of real-world situations will be critical to the effectiveness of translational neuroscience. Developing neuroimaging tools and in particular tools that function in a wide range of settings is a crucial component of such a capability and is a top research priority according to the Executive Office of the President [2]. In the final part of this session, two speakers will present improved tools for collecting and interpreting neural signals in real-world situations:

- Bret Kellihan and colleagues describe a neuroimaging tool for understanding the human brain's interaction with real-world stress [27]. While laboratory settings have offered a great deal of insight into the brain function underlying stress, the effectiveness of laboratory stressors to represent the entire span of real-world stressors has been called into question [28]. Mr. Kellihan presents a paper discussing the state-of-the-art in real-world stress measurement technologies and the limitations of current systems. He also describes the novel multi-aspect real-world

neuroimaging system (MARIN) that has been developed specifically for studying the brain under conditions of real-world stress. This tool will enable a better understanding of the neurological mechanisms of stress and enable the development of future neurotechnologies that function in real-world situations.

- Vernon Lawhern and colleagues focus on the critical issue of artifact or non-brain electrical signal identification within EEG time series [29]. Real-world environments pose critical issues with non-brain electrical signals that are dramatically different than the issues posed under laboratory conditions designed to minimize sources of artifact. Hence, real-world neuroimaging will require effective tools to eliminate or potentially separate and utilize the non-brain from brain electrical sources. Dr. Lawhern presents a study that focuses on identifying artifacts using autoregressive (AR) models and specifically proposes a method for determining optimal AR features based on a penalized multinomial regression. The authors' results indicate that the size of the feature vector can be greatly reduced with minimal loss to classification accuracy, which has significant ramifications for both computation efficiency and hardware design.

Together, these talks on neurotechnology development highlight translational advancements in BCI and real-world neuroimaging technologies. The multifaceted approach taken by the authors in this session demonstrates the importance of developing neurotechnology tools and methods to enhance human system performance as well as a means to measure the brain-in-action within ecologically valid environments.

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