The good placement

Knowledge Valorization

The principal motivation for the development of BCIs is to restore communication and control in the absence of words, gestures and other motor actions to people with severe neuromuscular disabilities (Shih et al., 2012). FNIRS is a promising functional-neuroimaging modality for this objective that has been used for BCIs in healthy participants (Naseer and Hong, 2013; Weyand and Chau, 2015; Batula et al., 2017; Nagels-Coune et al., 2017; Weyand and Chau, 2017; Sereshkeh et al., 2018; Rezazadeh Sereshkeh et al., 2019; Abdalmalak et al., 2020; Nagels-Coune et al., 2020) and in patients (Gallegos-Ayala et al., 2014; Abdalmalak et al., 2017). However, clinical applications of fNIRS-BCI systems suffer from a number of limitations that have slowed its translational potential. This dissertation outlined progress to overcome some of these limitations. First, we evaluated factors that could improve the feasibility of real-life fNIRS-based BCIs (**Chapter 2**). There we saw that participants can successfully control the BCI system by imagining doing a short task (mental imagery) and using a single pair of measurement sensors. Further, positive reports from participants suggest that augmented reality is a promising technology to enhance user experience for fNIRS-BCI applications. In the next chapters, we evaluated factors that can compromise fNIRS signal quality and its sensitivity to detect task-related brain activation, which is crucial to ensure a correct functioning of BCI systems. The way fNIRS sensors are arranged on the participant's head is one of such factors, and in this context, we investigated how different sensor placement strategies affect the fNIRS signal in **Chapter 3**. This study revealed that using gradually more individualized information obtained from the MRI scanner led to a better outcome, but that not all the information acquired at the scanner was required to achieve a robust setup. Another factor strongly influencing the fNIRS signal is the physiological noise such as heartbeat and breathing, to name a few. This physiological noise is measured at the same time as task-related brain signal by the fNIRS sensors, and it is not straightforward to tear them apart, which compromises our sensitivity to detect task-related brain activation. It has been suggested that the presence of vessels around fNIRS sensors can influence the amount of unwanted physiological noise, and in **Chapter 4**, we investigated precisely that. In addition, we tested whether the effectiveness of a physiological noise correction method named short-separation regression (SSR), which uses additional sensors placed on the participant's head, also depends on the proximity and density of vessels. The study verified that SSR improves fNIRS-signal quality and the sensitivity to detect task-related brain activation considerably and shows that signals obtained via these additional channels are affected by close vascular structures.

Short- and long-term impact

Although the presented work was framed in a communication and control BCI context, the knowledge gained here can be extended to other BCI applications. As indicated in Figure KV1, the most immediate beneficiaries of the work presented in this dissertation are other research groups working directly on fNIRS-based BCI for communication and control as well as neurofeedback. This is because all empirical chapters addressed challenges shared amongst these applications. Moreover, the findings from **Chapters 3** and **4** are applicable to research that focuses on the study of other (if not all) neural processes using fNIRS. These chapters provide insight to factors influencing signal quality and sensitivity to brain activation which is relevant to any fNIRS study. Specifically, the knowledge gained in **Chapter 3** will help researchers to efficiently utilize resources when designing fNIRS experiments. Meanwhile, basic methodological investigations like the one presented in **Chapter 4** will form the basis of fNIRS physiological noise-removal strategies in the future. These two chapters are further relevant for those developing tools to optimize optode layout design and fNIRS data analyses. In addition, we have purposely made the dataset from **Chapter 2** and probabilistic maps from **Chapter 3** available to support this progress.

Within the realm of BCIs, our work contributes to ongoing development of brain-robot interfaces and their extended range of potential applications in the many domains where robots are used. Examples include disaster management (e.g. remote control of robots that inspect dangerous or contaminated areas), industrial manufacturing (e.g. training robots to determine what is defective on a conveyor belt and remove it automatically based on a human inspector’s brain signals), entertainment (e.g. games with robotic agents) and healthcare (e.g. support for people with severe motor impairments completing daily-life activities or regaining functionality through neuroprosthetic devices).

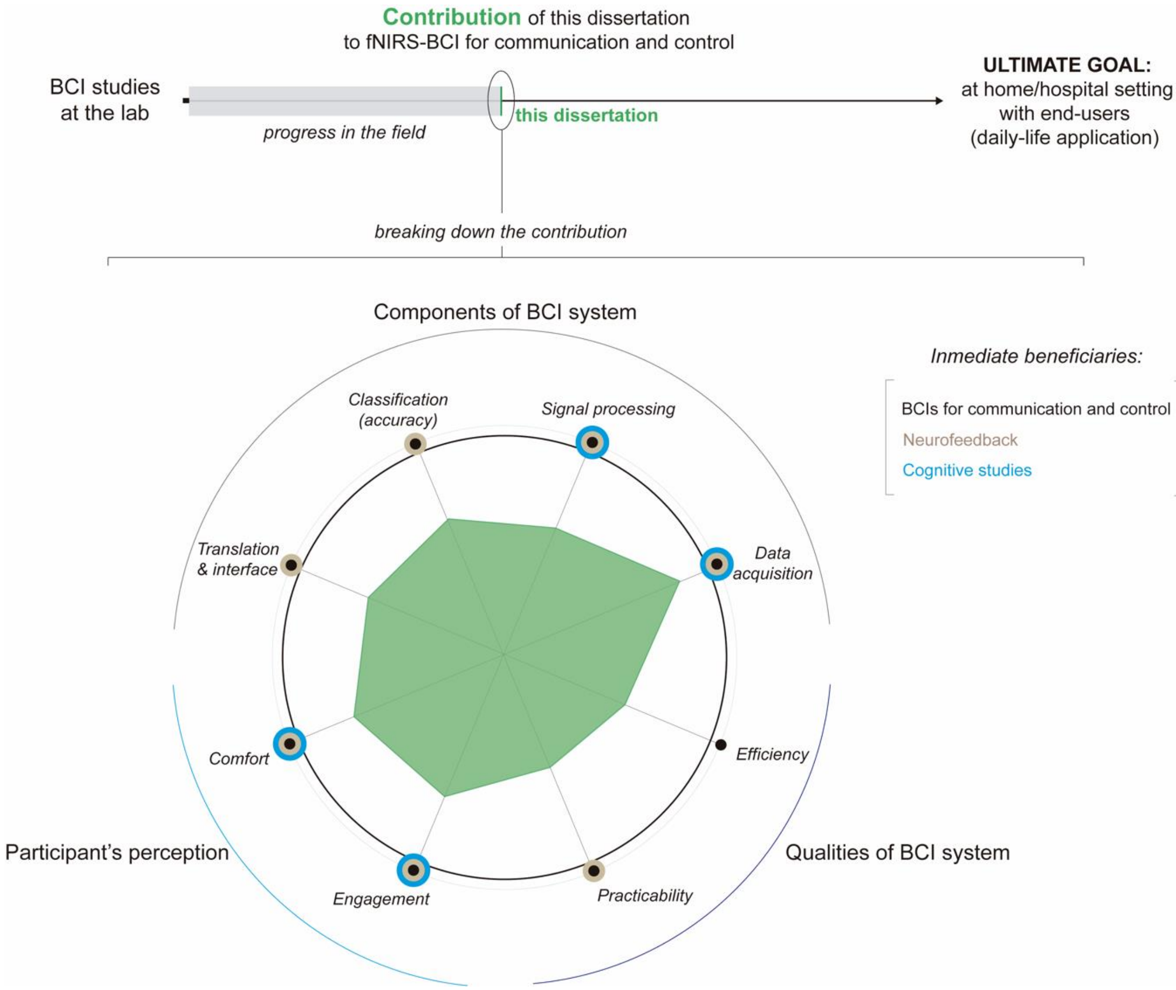

Figure KV1. Contribution of this dissertation and its immediate beneficiaries. The knowledge obtained in this thesis contributes to the advancement of data analysis and acquisition techniques to ultimately make fNIRS-BCIs applicable to everyday situations. The main contributions were divided into three categories, namely components constituting a BCI system, qualities of a BCI system and participant's perception. The polar diagram illustrates the contribution of this work regarding each subcategory. The concentric circles represent the immediate beneficiaries of this thesis: other fNIRS-based BCI researchers focusing on communication and control applications (in black), fNIRS-based neurofeedback applications (in beige) and other fNIRS-based cognitive studies (in blue).

The work presented in this dissertation can also benefit those with brain injuries and mental disorders. For example, patients with severe motor impairment (such as those with locked-in syndrome) have limited behavioral capabilities, yet it should be possible to express thoughts using preserved mental abilities (Sorger et al., 2012). Here, we worked to improve signal acquisition and analyses approaches while almost exclusively using mental tasks.

Together with the small optode setups featured in this thesis, we have set realistic foundations for applying our work in this and other patient groups sharing similar symptoms. Additionally, in **Chapter 2** we showed that AR technology can be successfully combined with fNIRS-BCI setups in the context of communication and control. Beyond these applications, AR technology can be used in neurofeedback therapy in patients suffering from anxiety disorders such as phobias to facilitate anxiety regulation. This is particularly interesting since AR provides a unique scenario where a realistic, anxiety-inducing stimulus can be presented in a controlled manner by imposing virtual stimuli, such as personalized threatening spider, over real objects and environments, such as the patient's arm (Gamito et al., 2011).

Future directions

A community effort

The ever-growing fNIRS community is well aware of the limitations of fNIRS technology and it has made collaborative effort to minimize and account for these. For example, several tools have been developed for designing informed and optimized optode setups that guarantee good signal quality and coverage (Machado et al., 2014; Aasted et al., 2015; Wijeakumar et al., 2015; Brigadoi et al., 2018; Machado et al., 2018; Zimeo Morais et al., 2018). A wide range of methods have been developed and implemented in analysis software to correct for the physiological and non-physiological noise sources, both offline (Homer 2 and Homer 3 (Huppert et al., 2009); Nirs toolbox (Santosa et al., 2018) and Nirstorm (Tadel et al., 2011)) and in real time (Lührs and Goebel, 2017). Further, validation and standardization efforts of these tools have promoted reproducibility. We hope that this collaborative effort will remain in the years to come.

Miniaturization of technology

Monitoring brain activity using fNIRS in real life situations has become increasingly accessible over recent years thanks to the development of miniaturized and wearable fNIRS devices. These systems do not use fiber optic bundles, making them more lightweight and more resistant to movement artifacts (Pinti et al., 2018). These are highly desirable features for real-life, fNIRS-based BCI applications, and we expect this progress to continue over the next years. Further, with the miniaturization of the technology and the improvement of neuronavigation systems and auxiliary measurement devices, we expect to see a more streamlined integration of these tools and fNIRS systems. Of particular interest for the future of BCI applications is the development of hybrid BCIs that combine EEG and fNIRS measurements. Previous work has shown that they can achieve better performance than with unimodal BCIs (Fazli et al., 2011; Khan et al., 2014; Khan and Hong, 2017; Shin et al., 2018; Rezazadeh Sereshkeh et al., 2019). However, these systems are not frequently used in practical applications because the amount of hardware needed to capture two different types of signals simultaneously results in bulky and complex systems. We hope that the progress in miniaturization happening separately for fNIRS and EEG systems is extended to their integration.

Need for user-centered designs

It is important to emphasize that more work is required to realize these goals since the knowledge gained in this dissertation reflects basic scientific investigations that will consequently benefit these target patient groups. We addressed some of the limitations currently faced by fNIRS-BCI applications that hinder the translational potential of BCIs. We did so in ideal laboratory conditions, measuring healthy, young, motivated individuals and having minimal technical and temporal constraints. Naturally, BCI researchers will need to seek collaboration in the future with end-users and, when applicable, with their immediate caretakers, family members and medical staff. Interviews, surveys and focus groups will help researchers and developers understand and identify the needs and reality of the users. Further, direct contact with end-users will enable researchers to iteratively validate the methodological developments. This user-centered design approach has the potential to yield higher user satisfaction and better system adoption (Sujatha Ravindran et al., 2020).

Our contribution as researchers

Since their inception, BCIs have inspired countless science fiction novels and movies and have attracted substantial media coverage and attention. This can be a good thing, particularly when BCI applications are represented positively. Such coverage draws attention to struggles faced by individuals that would benefit from this technology, thereby creating a social awareness and interest in technological advancements. It can also serve as a platform for publicizing opportunities for participation in research studies. However, the image of BCI technology portrayed in these platforms can reflect dystopian views. These scenarios rarely contain technological limitations such as low information transfer rates or signal quality-related problems, and largely ignore end-user discomfort. Importantly though, dystopian scenarios stimulate open discussions about ethical concerns raised by BCI technology.

Simultaneously, unrealistic descriptions of BCI technology can inflate hopes of potential and future end-users. BCI researchers are therefore instrumental, having the expertise to educate end-users and their immediate social circle (when dealing with clinical populations), as well as the responsibility to help them manage their expectations about the technology. This can be done in a localized manner (e.g. in the aforementioned focus groups and interviews), or in bigger settings (e.g. science communication events or media platforms). Regardless of the chosen output channel, it is important to find a good balance between exhibiting enthusiasm about progress and potential of BCI applications and openly describing the current limitations and state of the technology. It is equally important to consider primary users (end-users) and a variety of secondary users when applicable, as their contribution is essential to move toward mature BCI technologies.

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In the above reference list, 70.00% of <u>first</u> authors were male (vs. 30.00% that were female), while 93.33% of <u>last</u> authors were male (vs. 6.67% that were female).