Brain-Computer Interface Meets Information Retrieval: Perspective on Next-generation Information System

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Abstract

Information retrieval (IR) applications, such as search engines, ChatGPT, and recommender systems, have become essential tools for acquiring knowledge, making decisions, and solving problems. These systems have transformed the web into an external memory for humans, changing the way we think and learn from information. Despite advances in IR technology, the interaction paradigm between humans and information systems has remained largely unchanged for decades. Recently, with the development of neuroscience and biomedical engineering, it is possible to build a direct communication pathway between a computing device and the human brain via Brain-Computer Interfaces (BCIs). In this paper, we provide an overview of the application of BCIs in IR-related research. We identify three main opportunities for integrating active or passive BCIs into information systems: enhancing system control, improving user modeling, and enabling proactive system design. Additionally, we discuss example applications and challenges based on the proposed conceptual framework of BCIs for IR, and propose a research agenda for incorporating BCIs into IR systems.

CCS Concepts

• **Human-centered computing → HCI design and evaluation methods**; • **Computing methodologies → Artificial intelligence**; • **Information systems → Users and interactive retrieval**.

Keywords

Information Retrieval, Brain-computer interface (BCI)

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1 Introduction

In many scientific fictions, characters are equipped with Brain-computer Interfaces (BCIs) for communication with external knowledge and information. Recent research on BCIs encompasses an increasingly broad range of brain decoding methods [14, 16, 23], and even directly writing information into the human brain [8]. The scope of the above research generally focuses on how to decode brain signals as traditional interaction signals for input into information systems, such as motor instructions [1], language [14], and item selection [22]. However, the novel signals decoded from the human brain may directly transform traditional interaction paradigms of information systems by establishing several new pathways for efficient communication. Therefore, it is crucial to consider both the abilities of BCIs and how IR systems can process the BCI signals and further present more satisfying information to users.

On the other hand, IR systems have become "Cognitive Implants" (as stated by Turing Award Laureate Vinton Cerf), which can substitute for human memory and act as an external "brain". Recently, the technology for information systems has evolved to be more powerful and ubiquitous, from search engines to recommender systems and ChatGPT-liked chatbots. Despite many changes in desktop and mobile devices, the medium of interaction has remained relatively stable, specifically involving information input and content selection based on button selections on screen or keyboards. When BCI provides a new medium for information interaction, how to better couple BCI technology with IR systems, or design new interaction paradigms based on BCI, is still an open challenge.

Recently, some research has involved using BCIs for understanding and improving IR systems. These works can be mainly categorized into two groups: (1) understanding the cognitive basis of user behaviors in IR systems with BCIs, and (2) improving IR systems' service with additional signals collected by BCIs. For the understanding of user behaviors, BCIs help us to reveal the neurological aspects of relevance judgment [20], information needs [11], and satisfaction [18]. This provides insights for better understanding users' motivations and experiences when using IR systems. For the improvement of IR systems' service, the signals collected by the BCIs could help express the user's information needs and current states and enable the system to provide a more satisfying response. For example, Ye et al. [18] proposes to use the satisfaction predicted from brain signals for query re-writing and content-based recommendation. Eugster et al. [4] build a human-in-loop information recommendation system by predicting relevance judgments from brain responses.

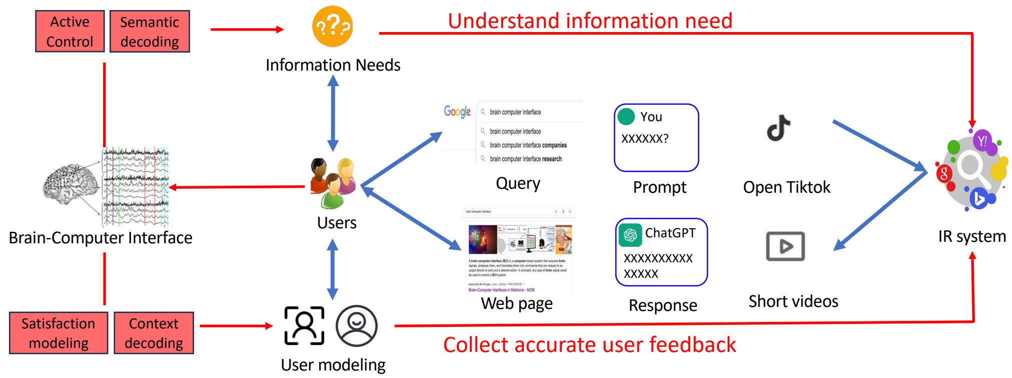

Figure 1: A conceptual framework in which BCIs may change traditional IR interaction process (Search engines, ChatGPT services, and recommender systems). Blue arrow indicates the traditional interaction pathways in which users and IR systems can interact with each other. For example, in a search system users can input queries into the search engine and interact with the Web page provided by the search engine. Red arrow reveals possible new information pathway (e.g., understanding users' information needs and collecting accurate user feedback) introduced by BCIs.

Figure 1 presents a conceptual framework for enhancing IR systems with BCIs. In addition to the conventional input signals (e.g., query, and prompt) and behavior interaction signals (e.g., click, touch, explicit annotation), the signals collected by BCIs introduce two typical pathways for enhancing IR systems. On the one hand, BCIs can help accurately understand users' information needs. Those BCIs can be broadly categorized into active BCIs and passive BCIs. Active BCIs require users' explicit involvement to actively control the search system, which can replace traditional input paradigms. However, actively inputting content may impose a significant burden on users. Besides, the input quality might be limited as most users are not good at prompt and query writing. Passive BCIs, on the other hand, directly decoding semantics or various user statuses from their brain responses to explain user's information need. For example, a query "apple" actively inputted by the user can be transformed into "fruit apple" when information decoded from passive BCIs suggests the users are hungry. On the other hand, BCIs can help collect accurate user feedback. The feedback signals provided by passive BCIs may help IR designers to better understand the users' satisfaction level and context information during the IR process. Furthermore, as the signals could be collected in real-time with BCIs, the IR system can even respond to the feedback and further provide more satisfying items. For example, an IR system can avoid providing similar responses when a response is decoded as bad based on BCIs' feedback.

In the rest of the paper, we first discuss the opportunities of BCIs for IR by revisiting existing efforts. We show that BCIs have been applied to enhance IR systems in three ways: IR system control, user modeling, and designing proactive IR systems. Then, we summarize the main challenges for constructing a BCIs-based IR system. Finally, we conclude the paper and give some current research directions that may contribute to future IR systems equipped with BCIs.

2 Opportunities of BCIs for IR

By revisiting existing efforts, this section discusses the opportunities of BCIs for IR from three aspects, IR system control, user modeling, and proactive IR system design.

2.1 IR System Control

Traditionally, people interact with Web Information by inputting instructions via keyboards, mice, and touch screens. Although most people adapt to this paradigm and learn how to use the tools for many years, this form of interaction may still be not human-friendly. In addition, there are many scenarios in which handed-based interaction is not feasible, e.g., disabled people, virtual-reality games, and military actions. Whether BCIs can be used to substitute the traditional way human users control the IR system remains an open challenge.

BCIs have the potential to be a medium for active instruction input. Existing research has shown that BCIs can be used in cursor control [23], which suggests that it's also possible to control information systems that can interact with the screen. Given that cursor control with motor imagination can be inaccurate, a recent study [2] proposes to use the steady-state visually evoked potentials (SSVEP) collected by electroencephalogram (EEG) devices to input the query and browse the Web pages, as shown in Figure 2. By adopting proactive query suggestions and auto-completion functions provided by search engines, users can input a query in an average of 5 seconds with an accuracy of 0.91. Although this performance might be worse than typing a query on a keyboard, it is already practically usable. In addition, attempted or imaginary speech decoding [8] is another promising pathway to transform brain signals into IR systems' instructions. On the other hand, BCIs could be used for conveying information from the IR systems to the user. Although relevant research is still in the preliminary stage, technologies such as transcranial magnetic stimulation (TMS) [13] have revealed a promising direction.

Recently, as BCI devices have become more portable, affordable, and quaint, using active BCIs for IR systems is also becoming

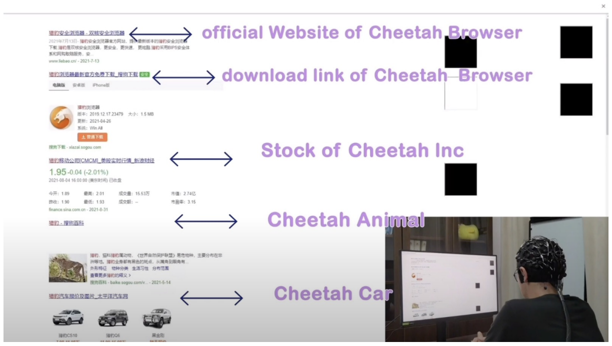

Figure 2: Example of Web Search with BCIs: The search system is controlled solely by brain signals in response to SSVEP flickers in the top right corner of the screen.

possible. Although it might be impossible to totally substitute the existing IR interaction paradigms in a short time, such evolution can first happen in several vertical applications. For example, combining BCIs with virtual reality devices [9] to free the hands in virtual reality games while still being able to query and interact with the system.

2.2 User Modeling

User modeling refers to estimating users' information needs, subjective experience, and context information during the search process. While using the current IR system interface, a user needs to formulate a text-based input (e.g., prompt or query) to represent her information needs. However, general users are not good at prompt or query writing, resulting in the input contents being unspecific and ambiguous. In addition, it is sometimes difficult for the user to formulate good input content when she does not have the necessary knowledge. Therefore, the IR system can not respond to satisfying content given the unspecific and inaccurate user inputs. Different from these text-box-based inputting interfaces, BCIs can provide richer information about users' information needs and search intents, in substitute of/in addition to the traditional input methods. Existing study has fulfilled this gap by augmenting text-based query with BCIs [16, 21] and inferring user-focused semantic contents with BCIs [18, 19]. For example, Ye et al. [16] applies a brain adapter built with a deep neural network to transform features collected from users' brain signals into a "brain prompt" that can be projected into a computational language model's framework. Then the text-based query and the "brain prompt" can collaboratively generate augmented queries that contain more accurate meaning and are easier for the search engine to find relevant documents. Ye et al. [18] proposes a query reformulation method using brain inputs with a transformer-based brain decoder and a language modeling approach. The reformulated query increases the top-1 accuracy of document ranking to 73.5%.

In addition to directly decoding semantics, BCIs can help to predict users' relevance judgment [5], stage of search [12], cognitive state [6, 7], and satisfaction of responses provided by the IR systems [18]. Such information could be used as feedback for the IR system to understand user engagements in IR systems and enable performance evaluation and system optimization. Although there has been extensive investigation into feedback in IR systems, including users' implicit behavior signals (such as clicks and dwell times) and the construction of Cranfield-style test collections with third-party annotations, these approaches are often inaccurate. Implicit signals are usually biased, and Cranfield-style evaluations may not necessarily align with the subjective feelings of real users. As an alternative, signals collected with BCIs are shown to be accurate [20]. [18] demonstrates that the performance of recommender systems can be improved by 25.4% using brain inputs, achieving results comparable to models trained with explicit user annotations on 30-40% of their interactions. In real-world datasets, explicit annotations can be acquired, and only a very small portion (usually less than 5%) of data has implicit annotations such as likes. Although the gain from brain signals is still limited due to their low signal-to-noise ratio, this issue can be resolved in the future with advancements in equipment and iterative improvements in algorithms.

2.3 Proactive IR system

Given the benefits in user modeling and IR system control brought by BCIs, it is then valuable to consider how the IR system can better response to the information decoded from BCI signals. The evolution of BCIs in IR can be happened in a lot of IR tasks, including query formulation, prompt writing, recommendation, and vertical IR scenarios. For example, Davis et al. [3] proposes to use a generative adversarial network (GAN) for automatic image editing applications enhanced by BCIs. Eugster et al. [4], Ye et al. [18] propose a query reformulation method based on the term importance estimated by BCIs. To explore how brain signals can be jointly modeled with existing IR systems which are built with implicit signals and Cranfield-style evaluation tests, Ye et al. [17] further propose a general framework that dynamically integrates different sources of signals by considering the information-seeking scenarios. By estimating the distributions of user signals in different scenarios, the optimal combination weights for various signals can be calculated using a pair-wise document re-ranking objective.

In addition to facilitating existing IR tasks, BCIs can bring new opportunities and formalize novel task in IR scenarios. For example, BCIs are known to be relevant to a series of cognitive concepts such as emotion [24], and cognitive bias [6]. These concepts are lack of research in the context of IR, and exploring how to utilize this information to build more user-friendly IR systems is a potential research direction. On the other hand, the usage scenarios of BCIs may differ from those of existing IR systems. Hence, formalizing the interaction scenarios in different IR applications is another promising direction. Moshfeghi and Pollick [12] firstly formalizes the applications of BCIs in IR by treating the search process as transitions between neural states. Such a formalization completely surpasses the interaction processes defined by system-based IR scenarios and may inspire new innovative designs for the proactive IR process.

3 Challenges of BCIs for IR

After discussing the feasibility and potential opportunities of BCI-based IR systems, in this section, we further examine the potential challenges.

As our ultimate goal is to build a BCI-based IR system to augment humans' cognition ability and help them memorize, learn, solve problems, and make decisions, the first challenge is to understand these cognition processes. Ji et al. [7] characterize the process in traditional Web Search scenarios into the realization of information need, query formulation, query submission, and relevance judgment. Although the process may vary in different IR applications such as recommender systems and ChatGPT-based chatbots, understanding these cognitive stages is always critical as it enables us to tailor the BCI-based IR system to better support each phase of the cognitive process. By dissecting and addressing each stage, we can develop more intuitive and efficient interaction mechanisms within the BCI framework, ultimately leading to a more powerful and user-friendly IR system.

The second challenge is balancing the ability to collect low signal-to-noise ratio signals while remaining portable, affordable, and convenient for existing BCIs. Current BCI techniques can be grouped into three major categories: invasive, partially invasive, and non-invasive. Invasive and partially-invasive BCIs usually provide more accurate signals compared to non-invasive BCIs but also suffer from the side effects of surgical interventions for collecting information from the neocortex. For example, Electrocorticography (ECoG) has been shown to be effective for semantic decoding [10] by measuring the electrical activity with electrodes embedded in a thin plastic pad and placed above the cortex. However, applications of invasive and partially-invasive BCIs are only possible for IR systems designed for injured people. On the other hand, non-invasive BCIs are considered safe and low-cost types of devices and have been used for a broader variety of applications. However, existing non-invasive BCIs are still far from accurate. For example, electroencephalography (EEG) is one of the most popular choices but its signals have low spatial resolution and poor signal-to-noise ratio. Hence, decoding performance with EEG inputs is no capable of instruction and semantic decoding with adequate accuracy at the current stage. Functional magnetic resonance imaging (fMRI) is another kind of non-invasive BCI that records metabolic signals and has higher spatial resolution. However, the worse temporal resolution of fMRI and the response delay of metabolic signals limit its application in real-time IR services. Although neural engineering researchers have made several advancements in collecting various types of brain signals, such as magnetoencephalography (MEG) and functional near-infrared spectroscopy (fNIRS), existing BCI devices still suffer from issues related to affordability, portability, and signal quality. Therefore, the commercial applications of BCIs in IR still require effort to devise better devices and corresponding decoding algorithms.

The last challenge is the application scenarios of BCIs for IR. Users may be reluctant to change traditional interaction paradigms as they are already adapted to them. In addition, convincing users to switch from familiar traditional paradigms to BCI-based interactions requires (1) addressing ethical concerns and (2) constructing more suitable usage scenarios. For the ethical concerns, the capability of BCIs to directly access and decode brain signals raises significant ethical concerns, as it could facilitate covert monitoring of individuals' thoughts, challenging the deeply ingrained notion of the mind as a private sanctuary, solely accessible to its owner. Therefore, the development of edge computing and encryption techniques is crucial for avoiding ethical issues, and society also needs to pay attention to control over companies developing related applications. For the usage scenarios, we foresee its applicability beyond traditional IR, which includes virtual reality (VR) applications, disabled services, military, and medical scenarios. For example, Tauscher et al. [15] investigates the feasibility of using virtual reality headsets to collect brain signals directly. As a scenario that naturally discard interactions based on keyboards and touchscreens, the interaction methods in virtual reality applications are not yet fully defined. Therefore, BCI-based interactions might be more easily adopted, especially considering that in VR scenarios, hands are often engaged in other tasks, such as driving or gaming.

4 Discussions and Conclusions

In this paper, we propose that Brain-Computer Interface (BCI) technology has the potential to transform the current search interaction paradigm. Literature reviews indicate that BCIs could feasibly be utilized as search interfaces, including aspects include IR system control, user modeling, and proactive IR system design. We propose that BCIs can address the limitations of existing IR systems given its novelty characteristics include hand-free interactions, cognitive process understanding, and real-time feedback collections. As illustrated in Figure 1, a conceptual framework IR systems can be enhanced by two pathways introduced by BCIs: understanding information need and collect accurate feedback, which have been long-term open challenges for the design of IR systems. In additional to traditional interaction signals, BCIs provide a special "explicit feedback" as it directly capture brain activities and are more accurate than implicit feedback signals (e.g., click, dwell time in search scenarios). Additionally, it does not require extra effort or a professional level of expertise from the user to provide explicit input and feedback.

Even though challenges still exists in understanding the cognitive IR process, developments of BCI devices, and application scenarios, we contend that with the BCI technologies available today, or those expected in the next decade, it is feasible to begin addressing some of the previously mentioned challenges. The integration of BCI with IR systems opens up new avenues for personalized and adaptive information retrieval and accessing. By leveraging real-time neural signals, IR systems can dynamically adapt to the users' current cognitive state, potentially enhancing information acquiring efficiency and user satisfaction. Collaborative efforts from neural engineering, information retrieval, and commercial organizations will be necessary to refine BCI and IR algorithms, improve the quality of neural signal, and develop robust evaluation methodologies to measure user experiences. By advancing BCI technology and exploring innovative IR applications, we can pave the way for the next generation of intelligent, adaptive, and user-centric information systems.

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