

SURVEY PAPER

Towards Canine Brain-Computer Interfaces (BCIs)

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ABSTRACT

Brain-Computer Interfaces (BCIs) have shown remarkable potential in human neuroscience and medicine. Yet, their application with animals, in particular canines, remains largely unexplored. This paper delves into the background, systems overview, implementation details, potential features, prospective use-cases and challenges, of canine BCIs. While the focus is on EEG-based BCIs, other modalities such as fNIRS are also discussed. Despite significant challenges, such as hardware design and data inference, I argue that canine BCIs hold potential to significantly push forward our understanding of canine cognition, and facilitate a higher bandwidth of human-canine communication, collaboration, and flourishing.

KEYWORDS

canine-human communication; brain-computer interface; canine cognition, canine computing interaction

1. Canine Cognitive Neuroscience

The field of cognitive neuroscience is relatively young, only receiving a name in the late 1970's by the ground-breaking cognitive neuroscientist Michael Gazzaniga, in conversation with the psychologist Geoffrey Miller in a New York City taxi [1]. Armed with electroencephalography (EEG), pioneered by Hans Berger in 1929 [2], as well as magnetoencephalography (MEG) [3], positron emission topography (PET) [4] and functional magnetic resonance imaging (fMRI) [5,6], cognitive neuroscientists perform empirical and quantitative analyses of internal processes [1].

While the focus of cognitive neuroscience is on human cognitive processes, with animal studies being used primarily as comparative evidence [1], a recent surge of interest in the scientific study of the behaviour and cognition of the domestic dog [7,8] has led to the birth of a new sub-field - canine cognitive neuroscience. A multitude of studies have used cognitive neuroscience tools and paradigms over the past decade to investigate a range of cognitive processes, beginning with Berns et al with the use of fMRI in awake, non-restrained dogs in 2012 [9], and followed by Kujala et al the following year successfully deploying fully non-invasive EEG with unsedated dogs [10]. Importantly, the focus of such studies has not been limited to comparing cognitive processes to humans, although dogs have been argued to be an excellent model for this purpose [11], but has also examined the unique features of canine cognition, including their novel cross-species relationship with humans. As such, researchers have investigated questions in domains such as voice-sensitivity [12,13], face-sensitivity [10,14–16], lan-

guage representation [17,18] and attachment and relationship dynamics with humans [19–22]. Two reviews of canine fMRI [23,24] and a review of canine EEG [25] further highlight the wide range of questions and paradigms that researchers have deployed in deciphering the canine mind.

1.1. Canine Neuroimaging Tools - Strengths and Weaknesses

1.1.1. Functional magnetic resonance imaging (fMRI)

The sophisticated functional magnetic resonance imaging (fMRI) has received greater attention than the dog-eared electroencephalography (EEG), with at least 33 papers published since 2012. Canine fMRI already boasts a dog-oriented magnetic coil [26], a tailored hemodynamic response function [27] and a tailored training protocol for dogs [28]. Such fervour can be explained by fMRI’s superior spatial resolution, which allows for the precise (and non-invasive) measurement of neural activity at the lower bound of millimetre voxels (volumetric pixels) engendering precise mapping models of neural activity.

However, fMRI has significant drawbacks. Foremost is it’s poor temporal resolution, that arises through it’s innate dependency on blood flow as a proxy to neural activity and restricts it to analyses in the range of seconds [29,30]. Moreover, the cost of procuring and maintaining a fMRI scanner, as well as the significant investment in training dogs, effectively limits it’s use to a handful of labs around the world and a few participants in each study. Small sample sizes are especially worth highlighting in light of recent discussion of the replication crisis in the behavioral sciences [31,32], which arguably affects cognitive neuroscience particularly hard [33], and fMRI research hardest of all. Recent work has claimed a minimum sample power of at least 100 participants [34] to be deemed replicable, a standard most fMRI studies cannot come close to, even with more modest criteria [35]. It is also worth noting that dogs capable of sitting motionless for minutes at a time in a noisy, enclosed space tend to not form a representative sample population. Finally, while fMRI studies could allow for discoveries into fundamental cognitive processes that could, in theory, furnish practical insights for working and companion dogs, it cannot be used outside the lab and is limited in real-world applications.

1.1.2. Electroencephalography

On the other hand, the seemingly ancient history of electroencephalography EEG [2] belies its potential power, especially when coupled with state-of-the art hardware, signal processing and machine learning algorithms. EEG possesses a high temporal resolution (especially compared to fMRI), with observations in the range of milliseconds allowing for fine-grained analysis of neuronal temporal features. This is one of the reasons EEG has a long veterinary history for the investigation of epilepsy and the prediction of idiopathic seizure events [36–38]. A second advantage of EEG is its accessibility and ease of use, with many robust research-grade setups costing between 1-10 thousand US dollars, around four to five orders of magnitude less than fMRI [39,40]. A third advantage is that canine subjects do not need to be extensively trained in order to collect usable data, allowing for a much wider, and more representative, pool of subjects. Finally, advances in human EEG technology [40–43], now enable data collection using wireless and gel-free systems in naturalistic conditions outside the lab environment.

However, despite some advantages, collecting and deploying high-quality neurological data using EEG comes with its own set of challenges. Unlike humans, canines have muscular and furry scalps that are prone to create artifacts and reduce the signal-to-noise ratio (SNR). Maintaining SNR is also a challenge in freely-moving and naturalistic paradigms, as motion is known to create artifacts. Because of fur, using gel-based electrode systems appears necessary in order to collect meaningful signal, creating inconveniences in collection of data. The large and non-linear variance in canine head shapes and sizes, ranging from dolichocephalic (greyhounds) to brachycephalic (pugs), means acquiring or designing standard headsets are a major challenge. Most importantly, EEG data has very low spatial resolution, with signals being the end product of the integration of postsynaptic potentials of thousands to millions of neurons traversing from the brain across tissue, bone, muscle, skin and hair [44], making the interpretation of this data challenging.

2. Canine Computer Interaction

While creating computing interactions with animals has a long history, capable of being traced back all the way to B.F Skinner’s work with rats in 1930 [45], Animal Computer Interaction (ACI) as a research discipline has only emerged during the past decade or so [46,47]. The key considerations that underlie the field today, and differentiate it from prior research, is the adoption of principles and techniques from Human Computer Interaction (HCI). This leads to a focus during designing computing devices and environments for animals to be ensuring the animal’s needs and perspective are central to the design process. That is, ACI emphasizes that animals are the *users of* and not the *objects within* computing interactions, and that researchers and developers should design for and with animals [47].

Within ACI research, canine computer interaction has emerged as an important and popular sub-field. Studies in canine computer interaction include — the development of wearable sensors to track data such as respiration [48], heart-rate [49,50], and posture [51]; environmental sensors such as cameras that monitor activity levels [52] and facial expressions [53]; and human-canine interfaces that enable communication across distances through the use of haptics [54], and custom devices [55–57]. Increasingly, sophisticated signal processing and machine learning models are being introduced to allow for insight and inferences that were previously inaccessible [53,58].

Some of the major themes in animal/canine computer interaction research are -

- (1) Agency and Autonomy - Animals make decisions and interact with computing systems independently. For instance research exploring how interfaces and sensors for dogs can allow them to express choices or needs, such as food dispensing, door opening, or initiating play, enhancing their overall well-being.
- (2) Welfare-Centric - Design considerations and outcome metrics align with enhancing or preserving animal welfare. The focus is on minimizing stressors and understanding cognitive limits in interaction with digital interfaces. Technologies like wearable sensors monitor vital health parameters and inform welfare initiatives.
- (3) Sensitivity to Sensorimotor Affordances - Interfaces are designed based on a animal’s unique physical and sensory capabilities. For dogs, this can include their keen sense of smell, limited color vision, or paw dexterity. This results in specialized hardware and software tailored to these specific capabilities and constraints.

- (4) Interdisciplinarity - Canine computing interaction combines insights from veterinary sciences, cognitive psychology, computer science, and engineering. Interdisciplinary efforts lead to nuanced understandings and effective designs that consider both technological and biological aspects of canine computer interaction.

3. Canine Brain-Computer Interfaces - A Natural Confluence

The rise of both canine cognitive neuroscience and canine computing interaction naturally leads us to the beginning of a new sub-discipline - canine brain-computer interfaces (BCIs). While still in its nascent stage, the development of canine BCIs is poised to rapidly grow with potential to fundamentally reshape the relationship between humans and dogs.

BCIs are devices that forge a connection between the brain and a machine [59] by utilizing advances in cognitive neuroscience to convert recorded mental activity into actions in the physical or informational worlds. A BCI system typically consists of sensors to measure brain activity, signal preprocessing and feature extraction algorithms to process data, and prediction software such as machine learning models to translate processed data into action-inducing output.

While no end-to-end canine-specific BCIs exists at this time of writing, advances in human BCIs have been tremendous, with many improvements in both hardware and software being capable of transferring across species. The rest of this paper will provide a thorough overview of the components, potential features and use-cases, and challenges of designing and deploying a canine BCI system.

Before continuing, it is important to note the two fundamentally different kinds of BCIs - invasive and non-invasive. Invasive BCIs can be defined as requiring the violation of the user's physical ontology for their function, i.e. they require an implant/incision to record data. These include neural implants, iEEG, and needle electrodes. On the other hand, non-invasive BCIs are capable of functioning without any alteration to the user's physical ontology and can be placed on top of the hair/scalp. These include clinical, commercial, and consumer EEG systems such as g.tech, EMOTIV, and MUSE, as well as fNIRS systems such as Artemis and Gowerlabs LUMO. In line with ACI principles, the focus of this paper will be only on non-invasive canine BCI systems.

4. System's Overview of a Canine BCI

A canine BCI, like human counterparts, requires two sub-systems, namely, i) hardware that comprises recording sensors and a digital amplifier, and ii) software that consists of signal processing and machine learning models. Both hardware and software need to be integrated together to facilitating data capture, analysis, and result delivery. A schematic of such a system is shown in Figure 1.

4.1. *Hardware*

The hardware component of a canine BCI consists of a headset with sensors that record activity from the brain and an amplifier device that collects, preprocesses, and transmits this data to an edge computing device. One instantiation of this device

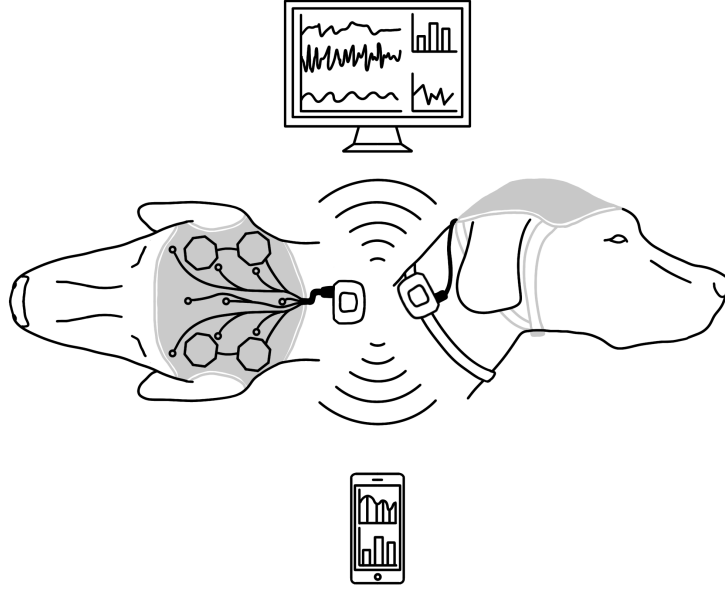


Figure 1. A sketch of a system’s overview of an example canine BCI system.

is depicted in Figure 2. Here, a cap design is utilized that can incorporate numerous customizations to cater to the varied anatomical diversity in dogs. Enmeshed in the cap are electrodes that can record relevant neural activity using electroencephalography. The data from these electrodes is pre-processed, amplified and digitized via a suite of signal processing algorithms in real-time, before being wirelessly transmitted. Further processing can then take place on the edge computing device, as described in the below Software section.

4.1.1. Headset and Sensors

The headset and sensors sub-system can take a variety of forms and utilize different neuroimaging methodologies. As the sensors have to be non-invasive, portable and lightweight, the two methods that can currently be deployed are primarily wireless EEG and fNIRS systems. Niso and colleagues [40] survey the recent developments in wireless EEG systems and find a large variety of research and commercial products available for human-use. While many of these systems come in form factors that are fixed and tailored for humans, some systems are modular and can be adapted for canine use. Similarly, while the majority of fNIRS systems can only be used with humans, recent developments allow for cross-species systems to be assembled, using do-it-yourself methods, such as those utilizing 3D printing [60], or modular systems that can be assembled in bespoke designs, such as the Gowerlabs LUMO system that has been used with infants [61]. Ultimately, bespoke designs for canine-specific headsets would be the preferable modality for collecting high-quality canine data.

A crucial consideration in the development of a canine EEG headset is the muscu-



(a) Prototype of canine EEG-BCI hardware



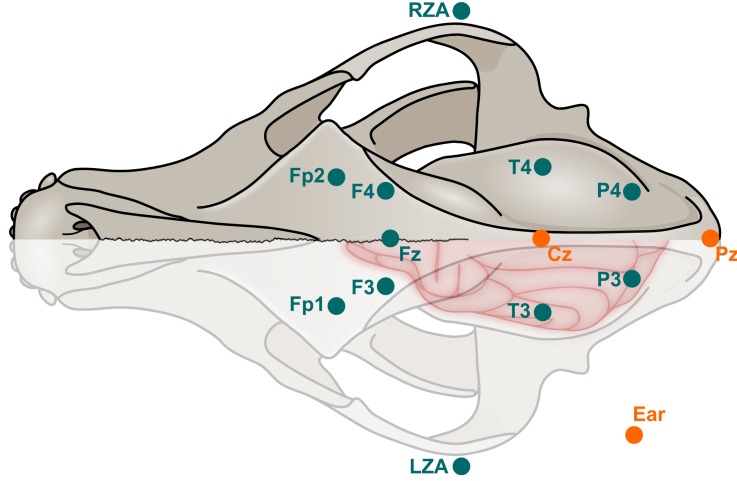
(b) Example of mounted prototype on an adult cocker Spaniel

Figure 2. An example canine BCI prototype consisting of an EEG sensor headset connected to an amplifier device.

loskeletal anatomy of the canine head. The variance of the dog’s head across breeds would requires headsets to be individually customized, or to consist of a large variety of breed-specific sizes. Moreover, imaging-specific challenges would have to be considered. As mentioned prior, EEG is susceptible to artifacts from the dog’s muscular scalp, and the montage of the electrodes should be tailored accordingly. In their 2023 EEG review, Kulgod and colleagues [25] provided a schematic of the various montages used by the 22 reviewed studies, which is shown in Figure 3. As depicted, the majority of studies utilized electrodes on the anteriorposterior midline of the skull, leveraging the bony ridge of the sagittal crest to reduce muscle interference and boost signal quality.

The review also noted that all non-invasive canine EEG studies deployed between 1-8 electrode channels, which is comparatively much lower than human setups, which tend to deploy between 4-128 channels [62]. The authors note however, that given the difference in cortical neurons between canines and humans, with dogs estimated to have 32 times fewer neurons than humans [63,64], a 4 channel setup in dogs can be considered to be a ‘high-density’ 128-channel system.

Finally, when building canine EEG headsets, the choice of electrodes is a crucial decision. Electrodes fundamentally vary along two dimensions - wet/dry and active/passive. Wet electrodes require the use of electrolyte gel to achieve sufficiently low impedance that is essential in recording high quality signal-to-noise ratio (SNR), whereas dry electrodes use compressed form factors that allow them to be used without any gel. Essentially, wet electrodes achieve higher signal quality by sacrificing convenience [42,43]. On the other hand, active electrodes utilize an amplifier pre-loaded into the electrode to boost signal quality, whereas passive electrodes do not have such capabilities. Here, active electrodes trade weight and cost for higher signal quality [65]. Given the aforementioned fur and muscle on the dog’s head, dry and/or passive electrodes may suffer from insufficient SNR and the optimal choice would be wet and



(a) An example of an individual figure sub-caption.

Figure 3. Different electrode montages used by the six technical setups. Electrode labels follow from the human 10-20 system, where letters indicate the lobe — Fp=pre-frontal, F=frontal, P=parietal, T=temporal, and C=center. The left and right zygomatic arch are also depicted as LZA and RZA. Odd numbers refer to electrode placement on the left side and even numbers indicate placement on the right side of the brain. Reference electrode positions are highlighted in orange. It is worth pointing out that large variance amongst canine breeds means the figure is not representative of all canine individuals.

active electrodes.

For canine fNIRS headset, a different set of considerations arises. fNIRS relies on the differential diffraction of light in oxygenated and de-oxygenated blood to detect and measure brain activity levels. Thus, variables that affect light absorption also affect fNIRS measurement. One such variable is the quantity, density and color of a dog's fur, with dogs having a dark, dense and large coat likely being more challenging to collect good quality data. The only published study using fNIRS with dogs in 2015 was not successfully in collecting useful data [66], but the technology and methods have improved dramatically since, and future efforts are likely to have greater success.

Interestingly, a growing trend has emerged of integrating method to develop EEG-fNIRS systems [67]. These hybrid systems take advantage of the complementary nature of the modalities, such as the spatial-temporal resolution trade-off, to lead to more robust imaging systems and higher quality data. Newer sensing modalities such as fabric electrode composites offer the possibility of future systems being conformable, comfortable and easy to design and use.

4.1.2. Amplifier

The amplifier sub-system of a canine BCI would not differ from a human amplifier. The only constraint would be the size and weight of the device being suitable to be attached to dogs of all sizes. As such, the amplifier should be designed as a centralized unit comprising five key sub-units -

- (1) An amplifier circuit - This component is tasked with increasing the strength of the neural signals picked up by the sensors, bringing them to a level that can be digitally converted and processed effectively.
- (2) An analog-to-digital converter (ADC) - This crucial part of the system is responsible for converting the amplified analog neural signals into digital format for further processing.

- (3) A signal processing system - This sub-unit, built around a microprocessor, performs the necessary computational work to process the digital signals. It applies algorithms that filter and extract features from the data which are relevant to the cognitive state being measured.
- (4) A wireless transmitter - This component of the system broadcasts the processed data to a separate receiver, which could be an application on a computer or mobile device. The wireless transmission allows for real-time monitoring and analysis of the data.
- (5) A power source - Typically, this is a battery that provides a mobile and independent energy supply to the system, ensuring its continuous operation without being tied to an external power source.

4.1.3. Software

Software forms an essential part of any BCI system. Neural data recorded and processed by the hardware must be further refined, analysed, and used to make useful and actionable predictions.

Signal processing can happen either on the device itself, or once transmitted to another computing unit or the cloud. While dedicated software for engaging with canine BCI data does not yet exist, tools and methods from human BCI research can be transferred over with modifications. Prior research with canine EEG data have relied on dedicated packages and pipelines (such as EEGLAB and FieldTrip) to analyze data. Such research has generally followed the below steps -

- (1) cleaning of the raw data, utilizing bandpass filters, artifact removal algorithms such as support vector machines, and signal-boosting techniques such as individual component analysis (ICA) and general linear model (GLM) algorithms to reduce muscle and ocular interference.
- (2) transforming of the cleaned data, using both time and frequency-domain transformations such as Fast Fourier Transforms.
- (3) extraction of features from transformed data, such as the power of certain frequency bands
- (4) analysis of features, either using static algorithms or from trained machine learning models, depending on the specific application and the nature of the data
- (5) generation of real-time or long-term predictions on current and future behaviour

Some systems opt for a more direct approach by feeding raw data into deep learning models. While this bypasses the need for data cleaning and feature extraction, it usually demands extensive training datasets. However, when well-executed, deep learning approaches can deliver robust predictions and may adapt better to individual variations in neural data.

5. Capabilities of Near-Future Canine BCIs

Based on the literature in canine cognitive neuroscience, animal cognition and human brain-computer interfaces, some predictions can be made of the near-future capabilities of canine BCIs.

5.1. Insight and predictions from sleep

The majority of canine-EEG studies have been focused on asleep cognitive processes [25]. Sleep data is relatively easier to collect, as motion is limited, and large quantities of data can be recorded quickly. From the literature, a canine BCI would be able to achieve the following capabilities -

- (1) Measure sleep macrostructure, such as the duration of time spent in different sleep stages, latency of onset and transitions between stages, and power spectral frequencies over the course of a sleep session. Using population-derived averages, a sleep wellness score can be calculated and used to assess sleep quality. [68–70]
- (2) Detect and quantify sleep spindles, which are thalamo-cortical bursts in the cortex in the sigma frequency range (typically 9-16Hz) [71] in canine sleep data.
- (3) Make predictions on physiological and cognitive traits based on sleep features. Previous studies have found that certain power spectral density bands, specifically beta and delta, correlated with learning rates [72], and that features of spindles, such as the frequency, density, and amplitude, correlated with cognitive traits such as learning gain [73,74], memory consolidation [73], cognitive ageing [75], and owner rated hyperactivity [76].
- (4) Make predictions on human-canine relationship dynamics based on sleep features. For instance, Kiss et al [20] found a relationship between the power spectral density and the willingness of dogs to perform tasks, irrespective of their owner looking at them, a measure of susceptibility to the audience effect and Carreiro et al [21] found a relationship with the degree of self-reported attachment towards owners and sleep macrostructure.

5.2. Stimulus identification

Different stimuli likely evoke differing brain reactions. With high enough resolution and sufficient data, brain activity patterns can be "reverse engineered" through the use of encoding-decoding brain models. Evidence that this is possible with canine EEG data is limited but suggestive. Balint et al found evidence that dog's evoked responses to human versus dog vocalizations produced differentiable event-related potentials [12]. In a pioneering series of experiments that were the first non-invasive canine EEG studies in awake dogs, Kujala and colleagues found that the evoked response to human and dog faces were significantly different [10,14]. In a later experiment, they were able to train support vector models (SVM) to predict the category of image (human face, dog face, object, scrambled) with an accuracy higher than chance, suggesting robust prediction on visual images from EEG data was feasible [15].

There are no existing studies that have explored the processing of smells in dogs through the use of mobile neuroimaging techniques. However, human studies suggest that EEG data can yield important insights into how odors are processed neurologically [77,78]. Gaining an understanding of how dogs' brains process smells could be crucial for a more comprehensive grasp of canine perception and cognition. Initial research using EEG on anesthetized dogs has shown encouraging results, indicating distinguishable neural responses to different stimuli [79]. Additionally, several fMRI studies have found meaningful neural activity in dogs when engaged in tasks related to their sense of smell [80–82]. It is possible that future research could reveal discernible neural features from different odours, allowing for the identification of specific smells from canine BCI data.

5.3. *Language learning and comprehension*

The goal of restoring verbal communication in humans through BCI technology has been a primary driver for its research and development. In the context of canine BCIs, while the application differs, there's emerging evidence suggesting the technology could decode aspects of language comprehension in dogs. Studies such as those by Magyari et al [83] have shown that brain responses differ between known and unfamiliar words, and the degree of word familiarity correlates with specific neural features. Similarly, research by Boros et al [18] has indicated that dogs employ complex cognitive processes similar to humans for word learning.

Such findings imply that BCIs could potentially map specific words to distinct patterns of neural activity in dogs. With enough data, machine learning models could be trained to recognize these patterns, enabling real-time monitoring of a dog's comprehension during training sessions. This could revolutionize how training protocols are designed and implemented. For instance, training strategies could be modified in real-time based on the dog's neural responses, making language acquisition more efficient.

Moreover, the EEG data could serve as a quantitative metric for evaluating the effectiveness of different training methods. By identifying what works and what doesn't at the neural level, training protocols could be refined and optimized, enhancing both the performance and well-being of working dogs.

5.4. *State and Emotion Recognition*

EEG-based BCI studies with humans have been used to quantify and classify various temporary mental states, including emotion, stress, aggression and focus. While no similar canine studies exist so far, evidence from these studies could be taken to suggest similar abilities, including -

- (1) **Emotion Recognition** - Human studies have demonstrated high levels of emotion classification accuracy through EEG, sometimes as high as 89% [84]. These studies often employ fewer channels (e.g., 16 or fewer) effectively [85]. Canine BCIs could provide a gauge of the emotional landscape of by providing an objective and neurologically-based understanding of canine emotions.
- (2) **Focus Measurement** - Correlations have been found between EEG data features and levels of attentional focus in humans. Specifically, certain frequency bands like alpha and beta [86], or alternatively delta and theta [87], have been indicative of varying focus levels. This could be valuable for assessing the efficacy of training sessions or operational focus in working dogs.
- (3) **Stress Recognition** - EEG has been effectively used to measure mental stress levels in humans [88,89]. For working or service dogs, real-time stress monitoring could help prevent overwork and alert handlers to elevated stress levels.
- (4) **Aggression Recognition** - Some evidence suggests that aggressive events could be predicted from single-trial EEG data in humans [90]. This has potential applications in managing aggressive behaviors in shelter dogs or during behavioral therapy.
- (5) **Hunger Measurement** - Specific frequency bands like theta and beta in the posterior insula have been correlated with measures of hunger in human studies [91]. This could find applications in automated feeding systems or health monitoring.

- (6) **Micturition** - Rat studies have indicated a relationship between EEG patterns and bladder pressure [92]. This could be useful in predicting when a dog needs to relieve itself, particularly beneficial for indoor pets or service dogs on extended duty.

5.5. Canine-Human Synchronization

Another line of inquiry is inter and intra-species brain synchronization. Known as EEG hyper-scanning [93,94], this involves the measurement of neural oscillations across two or more individuals in order to calculate the degree of neural synchronization between the individuals. No studies have been published that have explored either cross-species (human-canine) or non-human (canine-canine) neural synchronization. Establishing valid methods for comparing neural oscillations between humans and dogs would require rigorous investigation and methodological development, especially considering human studies have been critiqued for their lack of rigorous quantification [95]. However, hyper-scanning paradigms hold significant potential for advancing our understanding of the mechanisms underlying social bonding, communication, and cooperation between humans and dogs and have practical implications, particularly in the field of working dogs such as the development of assistance and therapy dog programs.

5.6. Internet of Beings

Enabling dogs to engage with digital platforms could allow them to interact with other devices connected to the internet. Basic functionalities could range from operating a pet door when they need to relieve themselves, to obtaining food from an automated dispenser when hungry. This setup could improve their well-being by granting them some level of self-determination and influence over their surroundings. Additionally, it could offer pet owners innovative methods to comprehend and meet their animals' requirements.

6. Use-Case Profiles of Canine BCIs

In the following section, three sketches of how canine BCIs could furnish capabilities that augment the human-canine relationship are provided, drawing upon the features described in the above section.

6.1. Detection Dogs

One of the most important and widely used tasks that working dogs are relied upon is the detection of specific life-forms, objects, and physiological states. These include explosives, drugs, scat of endangered species, the presence of diseases like cancer in humans, smartphones, paper money, human cadavers and many others. Here, the sophisticated olfactory capabilities of dogs are leveraged along with their willingness to work with humans to achieve specific tasks.

Canine BCIs could provide capabilities at various steps along the detection dog work-cycle by acting as a data-driven amplifier to the selection, training, and deployment of detection dogs. Considering each step in detail -

- (1) **Selection** - The failure rate of detection dog training programs can be considerably high, often as much as 50-60%. As training programs can be resource-extensive, this leads to inflated costs for such programs as well as a large turnover of dogs who require re-homing. Various studies have looked into methods of improving the selection pool of dogs that start detection training, including genetic approaches, handler and breeder surveys and data from wearable sensors, but it remains a challenge. Canine BCIs could provide vital data that could inform selection processes. Brain activity patterns during sleep could reveal measures of key traits, such as learning gain, memory consolidation, and the willingness to perform tasks, irrespective of human attention. Data during wakefulness from carefully designed experimental paradigms could provide a quantified and neural correlate of behavioral and genetic measures that could be used to create multi-modal prediction models of future performance.
- (2) **Training** - Current detection training generally focuses on teaching a dog to provide a consistent indication to a specific scent using positive reinforcement and clicker behavioural shaping. Training protocols can vary significantly from organization to organization and amongst handlers and no complete consensus exists on best practices. Canine BCIs could provide objective data on training efficacy and create a positive feedback that could suggest improvements to methodologies. This data could also allow for an individualized approach tailored to the specificities of each dog.
- (3) **Deployment** - With enough data, canine BCIs could provide the ability to decode the trained odor stimuli from real-time brain signals. This could remove the need for dogs to provide binary behavioral indications (such as sitting) and instead utilize predictions that would be digital and multidimensional. This could allow dogs to be trained and deployed for multiple odors, as well as taking the human bias from the handlers out of the equation. Moreover, real-time data from the dog's mental state, such as their stress and focus levels, could be incorporated into this indication, providing a confidence measure to their indication, as well as letting handlers know when the dog needs a break.

6.2. Assistance Dogs

Assistance dogs serve various roles to aid individuals with disabilities and medical conditions. These roles range from guide dogs for the visually and hearing-impaired to medical alert dogs for conditions like Post-Traumatic Stress Disorder (PTSD), Postural Orthostatic Tachycardia Syndrome (PoTS), Type 1 diabetes, and Addison's disease.

- (1) **Selection** - The selection process for assistance dogs can be costly and time-consuming, with high failure rates similar to detection dogs. Canine BCIs could offer data on brain activity during human interaction or task execution to inform the selection process. This neural data could complement current methods like genetic and behavioral assessments to form a comprehensive evaluation system.
- (2) **Training** - The training of assistance dogs involves complex sequences of actions, varying from navigation assistance to object retrieval. Canine BCIs could provide insights into the cognitive processes during training, allowing for optimization of training pace, sequence, and reinforcement methods.
- (3) **Deployment** - Assistance dogs often operate autonomously without human interpretation. Canine BCIs could translate brain activity into real-time alerts or commands. For example, in medical alert scenarios, the BCI could send a direct

- alert to caregivers via an app based on specific neural patterns.
- (4) **Hyperscanning for Pairing** - The relationship between assistance dogs and their handlers is critical. Hyperscanning could capture synchronous brain activities between dogs and potential handlers, offering another data layer for optimal pairing.
 - (5) **Emotion Recognition and Welfare** - Monitoring the emotional state of an assistance dog is crucial for its well-being. Canine BCIs can detect signs of stress or emotional strain and relay this information to the handler or caregivers.
 - (6) **Remote Notification Capabilities** - The canine BCI system could send notifications to a list of caregivers in situations requiring immediate human assistance, thereby extending the dog's ability to summon help.

7. Challenges

7.1. *Hardware Design and Limitations*

One of the foremost challenges in developing canine BCIs is the hardware design, which as mentioned previously, must accommodate a variety of dog breeds with differing head shapes and sizes. Unlike human subjects, who can relatively easily adapt to EEG caps or helmets, dogs may find these devices intrusive or uncomfortable, especially when worn for extended periods. Design considerations must thus include not just anatomical fit but also the dog's comfort and freedom of movement. In addition, the hardware must be robust enough to withstand the physical activity common to dogs but sensitive enough to pick up nuanced neurological data. Lastly, material selection is crucial; it should be both non-toxic and hypoallergenic to ensure the well-being of the animal subjects.

7.2. *Data Collection and Ground Truth*

Data collection in canine BCI research presents another significant challenge. Experimental conditions must be strictly controlled to minimize artifacts that can distort the data. However, achieving this control is more complicated with dogs, who may be less compliant than human subjects. In addition, the amount of data needed for meaningful analysis is often quite large, requiring multiple sessions that can be taxing for both the animal and the handler. The data structure must also be standardized across various types of experiments, subjects, and even data collection hardware, which adds another layer of complexity, and requires a standard data structure such as canine EEG-BIDS.

The challenge of ground truth represents a more fundamental challenge. Unlike human subjects, where self-reported experiences can serve as a reasonable ground truth for states like stress or focus, dogs cannot provide this type of feedback. Therefore, innovative approaches must be developed to map neurological data to observable behaviors or physiological measures. These ground truths are essential for training machine learning models and for validating the research outcomes.

8. Conclusion

As the field of canine BCI research is still in its nascent stages, the challenges are manifold but the potential rewards are considerable. From improving training methods to creating more effective working relationships between dogs and humans, the prospects are intriguing. The hurdles, including hardware design, data collection, and establishing ground truth, are substantial but not insurmountable. The advent of robust machine learning algorithms, increasingly sensitive sensors, and interdisciplinary approaches that combine insights from veterinary science, cognitive psychology, and data science could collectively contribute to significant advancements. As both the technology and methodologies evolve, canine BCIs hold the promise of transforming our understanding of canine cognition, behavior, and well-being, and enhancing the ways in which dogs and humans interact and collaborate.

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