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FRIENDs: Brain-monitoring agents for adaptive socio-technical systems

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Abstract. Brain-monitoring is quickly becoming an important field of research, with potentially significant impacts on how people will interact with technology. As understandings of the inner-workings of the brain become more accurate technologies are becoming more advanced, smaller, cheaper, and ubiquitous. It is expected that new forms of computing that take advantage of brain states will be developed. This will enable systems to be highly aware of user mental contexts (emotions, intentions, and moods). These systems would display higher autonomic behavior and would streamline user-interaction while managing the use of brain context data for applications and services. There are few studies of how to develop and make use of agent architectures in this new domain. Current approaches target a single user and application situation. To be ubiquitous it is unrealistic for applications to have specialized overhead for individual users. Personalizable, but distributed approaches are needed.

To realize a general purpose agent for brain-monitoring and management of brain context is the goal of this work. This involves the selection of a brain-monitoring paradigm, the selection of an agent architecture paradigm, an inferencing mechanism, and the combination of the three towards a unified framework. Core motivations are discussed, and an early agent framework design (FRIEND) is presented, along with proposed proof-of-concept applications for using brain context.

Keywords: Ambient intelligence, cognitive inference, context awareness, multi-agent systems

1. Introduction

The inner-workings of the human brain remains one of the great frontiers that could further the advancement of technology. Brain data has largely been unavailable to developers of computing systems. How and what people think, as well as their states of mind, mood, focus, and intentions represent sensitive, yet important, data elements. Access to brain data would be useful for novel software that could be streamlined to a particular user; an aid in a host of applications. A driver falling asleep at the wheel could be detected and awakened before an incident. A nurse overworked and unable to focus well could be given rest breaks before administering incorrect medicine or dosages to patients. An important interface could filter away non-critical information from a pressured worker. These kinds of automated control actions were once fiction, but can be realizable today, because of brain data.

Technologies, like electroencephalogram (EEG), functional near infrared spectroscopy (fNIRS), and even functional magnetic resonance imaging (fMRI), are becoming smaller, cheaper, and easier to work with [7,19,55]. This means that mobile brain scanning for commercial everyday applications is on the horizon, and with it is a host of interesting research problems.

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Making sense of brain context on the fly (states and patterns of activity) requires adequate measurement methods, inferencing techniques, and a control architecture that captures these signals and makes use of them. The measurement methods are available, as well as inferencing methods [7], but robust control architectures that are flexible, fast, autonomous, and applicable in multiple scenarios remain to be explored. At present individual researchers are developing custom solutions for handling brain measurements [24,55,56] but no general-purpose architecture has emerged. This research aims to fill this gap by exploring architectures and developing a novel agent-oriented approach to brain-monitoring and brain context management systems.

2. Motivation

2.1. Socio-technical systems gaps

This work aims to seamlessly bridge the gap between people and technology from a techno-centric viewpoint, through smarter, human-context-aware computing. Its purpose is to augment social systems with more dynamic and flexible technology. At a high level there are three key issues. First, there are significant failures due to the misfit between technology and social context (i.e., the socio-technical gap between users and technologies). Second is that although these gaps can be minimized, there is only so much that can be done by modifying social systems to fit better with technologies. Third, there is a real challenge in designing, developing, and testing technologies that minimize the socio-technical gap.

Failures due to socio-technical disharmony have been discussed by Vicente [75], as stemming from five core layers (physical, psychological, social-team, organizational, and political), and range from being simply annoying to catastrophic. These result from flaws in both human social systems and supporting technologies, in particular computing technologies. On the human side there are limits, task overloads, attention overloads, and mismatched mental models [39], each contributing to potential failure points wherein people make mistakes due to excess demands, improper understanding of system states, tasks, and situations. On the technological side these problems are compounded by interface complexity and inefficiency [10], tasks out of context with situations, and the sheer increase of speed, data volume, and ubiquity.

Socio-technical gaps can be minimized through development of either smarter social systems, or smarter technology. Since social systems are limited in terms of human cognitive and physical capacities (such as stress, situational, or relational limits), it is realistic to focus on the development of smarter technologies to bridge the gap. Technologies like this would perform tasks related to monitoring human limits, predicting the state of the social (human) system, protecting the social system through useful interventions/actions, and assisting the social system through anticipatory actions where possible.

There is a need for software systems, as technology progresses, to understand human social systems, which are not well defined, yet highly dynamic, in many contexts and multiple environments, involved in potentially large complex and also multi-dimensional social networks (see [47,75] for more on dimensionality of social systems). In order to succeed in this task these systems must themselves be highly dynamic, autonomic (self-*, [36]), and context-sensitive (especially for human-context, device-context, and situation-contexts). In this work these capabilities are considered as “human-awareness”.

2.2. Brain cognitive context awareness

Developing high human-awareness systems is a big challenge, and remains a novel problem related to the overarching goal of improving the socio-technical gap. Human-aware systems must understand and

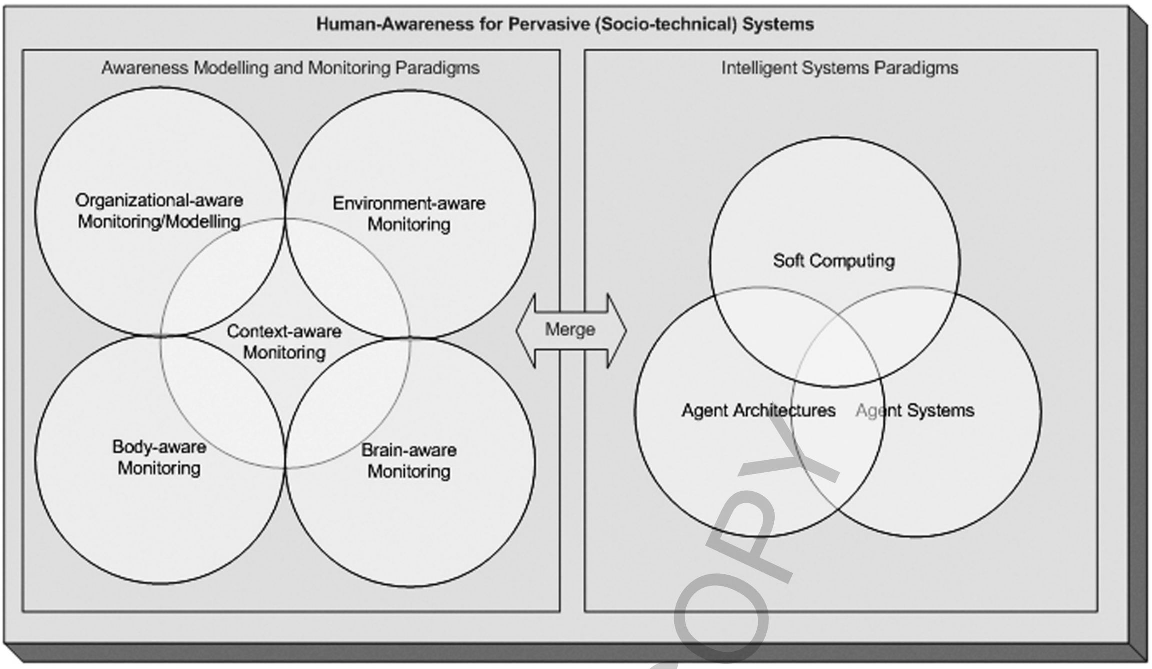

Fig. 1. Literature for the project involves a merger of context-awareness and intelligent agents.

react to human contexts. This refers to cognitive contexts (and emotional contexts), as well as physical, relational (social), and situational contexts. Of all these kinds of contexts to keep track of one of the most difficult to explore has been the cognitive context.

The cognitive domain remains fuzzy and interdisciplinary, a subject which is still in disagreement by the main proponents (i.e., knowing precisely where cognition comes from and how emotions and consciousness arise from the activities of the brain). Despite this, systems that could make sense of this kind of context could prove useful for understanding users at a level that would make significant applications possible. Cars that would be able to alert drivers of dangerous energy levels, or brake if attention is not focused. Hospital workers that could know their level of overload to a high degree could prevent casualties due to stress related mistakes in treatment, improving the "visibility" of stressful situations. Understanding the cognitive states of others is valuable information which has been largely unavailable to the general public for a host of reasons. Technologies are finally cheap enough, small enough, noise resilient enough, and power-efficient enough to be useful in everyday applications.

In a ubiquitous/pervasive system the cognitive context aware system would be a smart user assistant or a service for other applications. Architectures are needed to monitor, infer, learn, make decisions, and take actions on behalf of users, based on their cognitive and emotional states. Approaches to make sense of these cognitive contexts are needed to bridge the socio-technical gap in an important way, making software more aware of users in an intimate and deep way. This is the problem being addressed in this work.

3. Background

This research targets the intersection between the general disciplines of awareness modelling/monitoring and intelligent systems paradigms (see Fig. 1). The development of the agent architecture for brain monitoring centers around four themes, i) ubiquitous brain sensing technologies, ii) cognitive state estimation, iii) hybrid control architectures for context awareness, and iv) application specific uses of brain context. This literature summary is ordered as such; the final analysis is that a) research on brain sensing for ubiquitous domains is new, b) generally applicable approaches are unavailable, and d) hybrid BDI and soft-computing agents are not common for brain context management.

3.1. Ubiquitous brain-sensing technologies

Technologies that make use of the brain are still actively being researched, but can be divided based on their input and output interaction with the brain itself. Brain computer interfaces (BCI), for instance, are defined according to the following definition: “A BCI is a communication system in which messages or commands that an individual sends to the external world do not pass through the brain’s normal output pathways of peripheral nerves and muscles” [7]. Sending commands intentionally as output to control a device distinguishes a BCI from other similar technologies. Passively monitoring the brain, and making actions based on non-intentional signals, represents a slightly different domain [7]. Both make use of inputs from the brain, but intentionality is the distinguishing factor. This work fits in the second category of sensing non-intentional, non-control signals from the brain.

However, there have been very significant advances in the field of brain sensing and BCI that relate to this work. The development of non-invasive brain sensing techniques have advanced to the point where it is arguably on equal footing with invasive brain sensing techniques [7], when enough sensors are used. Invasive brain sensing (for BCI or otherwise) is among the earliest techniques, involving surgical implantations of sensing devices directly into the brain, either on the surface with electrocortigrams (ECOG), or within the tissue with intracortical sensors [25]. The results have been high fidelity signal detection. Recently, instead of sensing only, activators/stimulators (i.e., brain stimulator chips) have been implanted [52]. These kinds of devices have been shown useful for providing feedback to the brain (for controlling devices, etc) through intra-cortical stimulations [57].

Non-invasive brain sensing operates on a surface/scalp level, detecting brain activities according to signals emitted by the brain during operation. These signals are captured in several ways. One technique involves electroencephalography (EEG) waves; electronic signals detectable from the scalp with various sensor technologies. This is an established method that is very common in literature [26], despite being subject to noisy signals from muscle movement and eyeblinks. A second approach involves measuring brain activity according to the change in blood oxygenation levels. Functional near-infrared spectroscopy, fNIRS, performs this kind of detection using light-wave reflections to distinguish between blood oxygenation levels near the brain, which has been shown to correlate with brain activity [55,73]. These two approaches, EEG and fNIRS, have minimized equipment, involving sensors that are now wearable. In recent work they have been attached to headbands [2,55], and wireless headsets, such as the Emotiv Epoc [1], and the Neurosky Mindset [2]. However, only the EEG headsets are currently commercially available, and low-cost.

Other non-invasive brain sensing techniques require large devices such as magnetic resonance imaging (MRI) equipment, and positronic emissions topography and cat-scans (CT/PET). These provide high resolution images of the brain, but are not useful in a ubiquitous setting since the equipment is large [77]. This is important to mention, since in the past most brain sensing was primarily for research and rehabilitative purposes, such as disabled and locked-in patients [26], and have only recently been targetted towards everyday, non-rehabilitative uses. Ubiquitous brain sensing technologies are just becoming the focus of BCI research, as seen in surveys like [7]. For instance, brain data has recently been combined

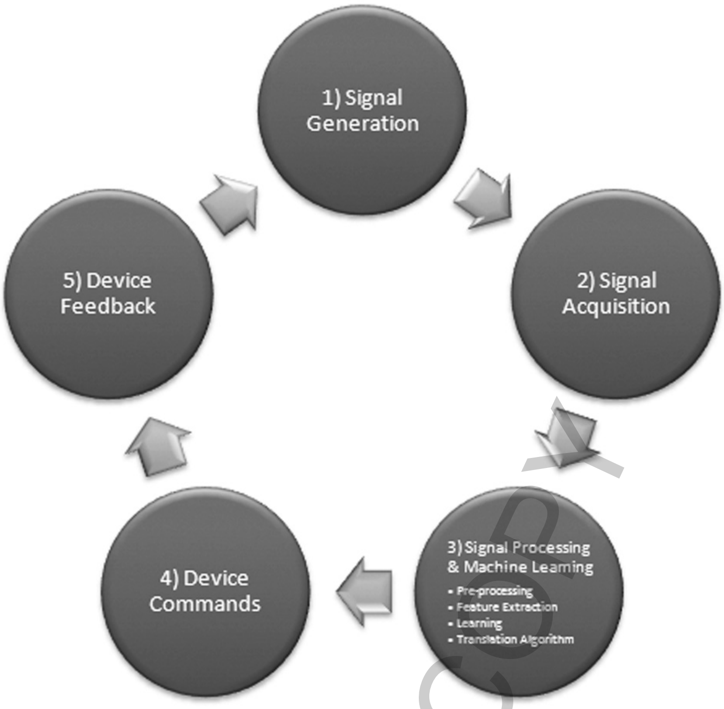

Fig. 2. The brain-computer-interface process, as seen in [26].

with mobile phone applications, although these are primarily only for showing states of relaxation, or activity [56]. These applications are very few but, with recent commercial availability of headsets, are becoming more practical [7].

3.2. Biosignals and cognitive state estimation

Understanding human behavior is a large and open research area in artificial intelligence, particularly for anticipation of affective and cognitive states, and approaches are still early, as seen in [54]. In terms of biosignals, various sensors may be used such as cardiovascular activity, electrodermal activity, skin temperature, respiration, and muscle activity, in order to classify features associated with emotional and cognitive states [14]. However brain monitoring allows for signals classification directly from the cognitive source.

The procedure for making use of data read from the brain has become a common process found in many BCI projects [26]. This involves stages of signal acquisition, signal processing, and some form of signal results usage. Signal acquisition has been discussed above. Signal processing for brain information involves pre-processing, feature extraction, and classification (or translation of signal features into state patterns) for use in system decisions/commands. These are standard techniques, and have been described in works like [28,41,66]. See Fig. 2 for an overview of the brain computer interfacing process.

As mentioned, in this work the focus is not on command and control of devices via a BCI, but rather decision making and shared control of devices based on brain data. Hence it is the stages of signal acquisition, and signal processing that are relevant from this field. Cognitive metrics are available based on spiking brain signal patterns known as evoked potentials, or sensorimotor rhythms [25], such as the steady state visually evoked potential (SSVEP) (based on visual attention), the P300 wave (based on selective attention), slow cortical potentials (SCP) and others (based on training), as well as event related (de)synchronization (ERD/ERS), based on imagined movement. These can be seen in more detail in [25], and classification algorithms are developed [21].

For instance the field of augmented cognition is based on the notion of using "cognitive state gauges" as estimates of user cognitive loads for different applications [34,67]. There has been much research on augmented cognition [61,62,67,68], and a number of gauges of cognitive load have been investigated. Among these, EEG and fNIRS are found to have statistically significant effects on relating cognitive workload to tasks [34]. The EEG measures considered in this study [34], were percentage high vigilance, probability low vigilance, executive load, and several event-related potentials. Also, in [21], cognitive load was assessed according to power spectral density analysis (PSD) of EEG channels at different frequency bands. Relaxation, communication, counting, navigating and visual search tasks were classified successfully, despite environmental/situational noise. Frequency bands have been associated with brain states such as attention, and working memory [9].

Also, in [22], error related potentials have been identified, both feedback errors, as well as observed errors, as particular spikes that take place only when a user discovers a mistake while controlling a device such as a shared BCI controlled wheelchair. In [74], fNIRS is used to detect mental states during multi-tasking as a foundation for brain-based adaptive user interfaces. In [27], working memory load was classified using EEG while performing cognitive tasks. In [38], task classification is conducted using EEG data for classifying rest, mental arithmetic and mental rotation tasks. These and other studies show that it is possible to classify several user cognitive states from brain activity.

3.3. Hybrid control architectures for context awareness

In this work the focus is on the development of a hybrid control architecture that acts as a broker and intermediary for EEG related cognitive state information between user and application; the core component in a cognitive context awareness system.

3.3.1. Context and context awareness

Context has increased as an area of study since the 1990's, and is generally defined according to Dey and Abowd [5], as "any information that can be used to characterize the situation of an entity". Context includes location, identity, activity, and time, as a means of describing the situation, essentially "what the user is doing" [5]. Systems that display context awareness are those which use any form of context data to assist a user in their tasks [5]. Context awareness research aims at providing systems with structures and concepts required in order to process information related to its operational environment, and the objects and people within that environment. This focuses on the improved understanding of situational states, and system user states of body and states of mind. These systems can then be more autonomic and adaptive, having a higher "resolution" of a situation as it develops. Research in this area is vast (see [32] for a survey, and [23,42,44] for further definitions. Figure 3 shows the context awareness problem graphically, highlighting the mental states as the target aspect.

In the last decade there has been a significant trend towards the development of context awareness in a range of scenarios. In [32] the authors survey the field from 2000 to 2007 and show that research in this area has increased steadily, and is divided towards four layers of, core concepts and research, network infrastructures and sensing, middleware (various kinds), applications, and user infrastructures and interfaces. The general need for context in applications is accepted and well discussed as a continuing field. It is noted particularly, that context modelling and reasoning requires specialized techniques, as presented recently in [11]. Such systems are required to deal with heterogeneity in information sources, mobility

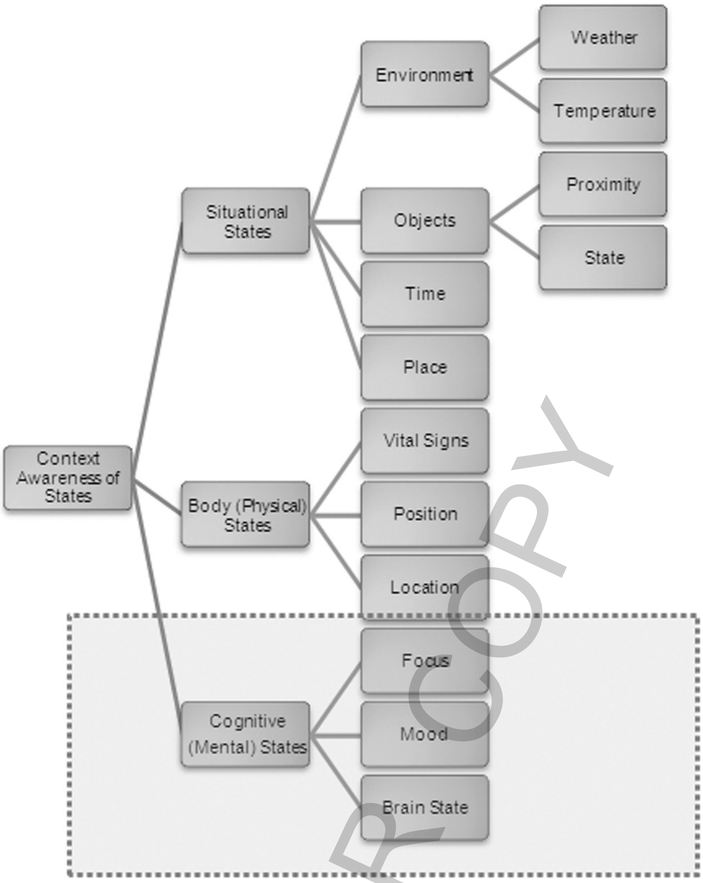

Fig. 3. The context awareness of states involve situational states, body, and mind states. The dashed line shows the focus area on mental context.

of users, relationships between different data sources, timeliness of data (context history), imperfection and incompleteness in data sources, reasoning for adequate decision-making, usability (for modelling formalisms), and efficiency in providing context information.

These works show that researchers have centered on approaches to context awareness that are based on object-role models, spatial models, and ontological models, as well as a number of abstraction mechanisms. Context must abstract from low-level sensory data, to higher level semantic interpretations, and further deduce situational relationships. Finally these systems must handle uncertainty, and a host of techniques have been developed which make use of fuzzy logic, probabilistic logic, Bayesian networks, Hidden Markov models, and Dempster-Shafer evidence theories [11]. Particularly expressed is that hybrid approaches are needed that can leverage advantages of multiple approaches towards meeting the large set of requirements for context awareness systems.

3.3.2. Hybrid soft-computing for context awareness

One approach to context modelling that has been proven is that of soft computing. Soft computing involves the combined research domains of Fuzzy Logic, Artificial Neural Networks, and Evolutionary Algorithms. These are well established fields that have been described in detail [45,71], particularly for purposes of classification, inference, and pattern recognition (such as speech analysis, image and facial recognition). Hybrid Fuzzy Inferencing Systems involve combinations of these fields resulting in improved capabilities. For instance, artificial neural networks provide machine learning capabilities as universal classifiers, while fuzzy systems act as problem solving agents that work well with uncertainty in data through rule-based logic and membership functions that take on a range of acceptable values [45, 70]. Evolutionary algorithms are useful for evolving an optimum architecture for a neural network [45].

Hence these three provide mechanisms that are a good fit for the context awareness problem, and have been employed in this direction with the recent increase in context awareness research. Classification of biometric signals is one type of context problem that has been shown to use hybrid neuro-fuzzy techniques [45]. In [8] the authors show a fuzzy inference engine for situation awareness using semantic hierarchies, fuzzy rules, and neurofuzzy classifiers. In [13] fuzzy classification is shown for dynamic environments that rely on fuzzy min-max neural networks. In particular the author provides an algorithm for incremental fuzzy classification allowing systems to adapt internal fuzzy rules over time based on situational inputs. This implies that hybrid neurofuzzy systems can remain in synch with current contexts. One relevant study involves [31], where fuzzy clustering of EEG data with a neural network was found to correlate with five mental tasks, and a fuzzy inference system was presented. Finally, in [80], dynamic fuzzy logic is presented for the development of a context awareness agent system for inferencing stock market fluctuations. These all highlight the usefulness of soft-computing approaches, particularly hybrid approaches, for context awareness problems very recently.

3.3.3. Hybrid agents for context awareness

Agents are largely considered as hardware or software control paradigms that have degrees of autonomic, social, reactive, and proactive behavior [78]. Although this is a general definition, it is extended with the addition of notions of belief, desires, and intentions [60,78]. These systems have been developed, in the 1990's, concurrent to context awareness research and represent a significant field with contributions to distributed artificial intelligence, robot control, modelling and simulation, human-agent teamwork, and even wireless sensor networks [6,18,46,47,50,72]. The field targets theoretical developments for reasoning with agents, agent architectures for designing such agents, and agent languages for programming and implementation [78].

Agent theories have roots in modal logics, particularly possible worlds theory, as discussed in [59,60, 78], which led to the development of popular agent architecture research. In [15], agent architectures are defined as design methodologies that must continuously "transform perception into a useful mental representation R; apply a cognitive process f to R to create R', a representation of desired actions; and transform R' into the necessary motor or neural effects." The author also reviews four core architectural paradigms based on research trends: the behavior-based AI, two and three layered systems, belief-desire and intention (BDI) architectures, and Soar/Act-R. Hybrid approaches, as well as architectures. The work highlights that agent design methodologies, although different, may be considered according to modularity of design and control, hierarchically organized action selection, and a parallel environment monitoring system. The work is relevant as a general overview that highlights the development of the BDI architecture, which is a selected framework for this research proposal.

BDI agents, have been proposed in [60], as a "Pneulian reactive system" based on modal logics and the subsequent development of a BDI agent language, Agentspeak [59]. The work in this area has been accepted by the community and has been translated into agent programming languages such as JASON [12], Brahms [17], and AgentFactory [53]. There are a host of logic-based languages that have been developed for programming agent systems. These have been recently surveyed in [49,64].

Context aware applications are closely intertwined with agent technology since the development of Dey, et al's, conference assistant [20], and in general a context-aware application fits the previous definitions of an agent application [15,78]. As such, hybrid soft computing approaches to context can benefit from agent architectural developments, particularly when multiple distributed agents are involved, as is the case for a ubiquitous context management system. Hybrid soft-computing systems are partially autonomous, and reactive inference systems, whereas agents must be also be proactive (goal oriented) and social. Also, many context problems can be described/modeled easily based on higher level BDI languages such as Agentspeak [12]. However, BDI agent systems have proven to have large overhead costs in development, as they must track large amounts of belief data, active goals, and active plans (sequences of actions already in progress but not necessarily complete). They could benefit from the efficiencies of the soft-computing approaches.

There have been several works which demonstrate mixed agent-oriented and soft-computing approaches, such as [80], where an agent is combined with a fuzzy logic approach towards predicting the stock market. These have been presented as early as 2004 where, in [69], the agent fuzzy decision-making framework is presented and the authors highlight that agent decision-making is an inherently fuzzy process and propose a fuzzy-bdi agent interpreter. In [63], an agent's model of uncertainty is presented using fuzzy set theory to provide the uncertainty-handling benefits of fuzzy logic to agent systems. In [29], a neurofuzzy BDI agent model is applied to the problem of controlling a simulation of an autonomous underwater vehicle. In [43], a neurofuzzy BDI agent has been presented for scheduling and assigning berths for vessels in container terminals, based on changing environment data. In [37], a neurofuzzy controller is combined with a BDI agent architecture for plan automation.

Although the benefits for crossovers between hybrid soft-computing-agents is clear, there remains the need for an architecture that provides these capacities and can be implemented and generally applied/programmed. Also, the use of such an agent in an active context management system is still an open area of exploration. This work fits in this domain by targetting the development of a hybrid-neurofuzzy-BDI-agent for context awareness of brain EEG data.

3.4. Related work on uses of brain context

In this work the applications of interest are those related to passive monitoring and alert, noise and distraction filtering, and shared control, all based on EEG context and cognitive state estimates. These general uses, see Fig. 4, range from safety calculations for monitoring, intervention, interruption, and filtering information for a user, in various domains.

Research in this area is only just beginning to be actively realized, with the development of the bodynet [79], where the miniaturization of wireless sensing technologies have enabled wearable wireless sensing devices. Today large projects such as the EU Guardian Angels initiative [3], are beginning to target the goal of personal smart agent assistants. Similarly the emoBAN work of [76], aims to develop methods of psycho-physiological mobile computing, although agent approaches are not a focus. Further, the augmented cognition (Aug-Cog) field has a related vision for adaptive systems based on brain and body information and has shown a number of related works towards these systems [61,62,67,68], but a general-purpose and hybrid agent approach remains an open area of research [35,51].

In terms of mobile devices and EEG waves, the work of [56], develops an EEG system involving the Emotiv EPOC wireless headset [1], for emotion measurement using spectral analysis and Bayesian systems as a classification method.

In the work of [55,73], a mobile fNIRS system is used to adjust visual representation of data to fit user cognitive strengths, and also for real-time task classification. Also, in [33], a real-time BCI is developed on PDA hardware and used for game control.

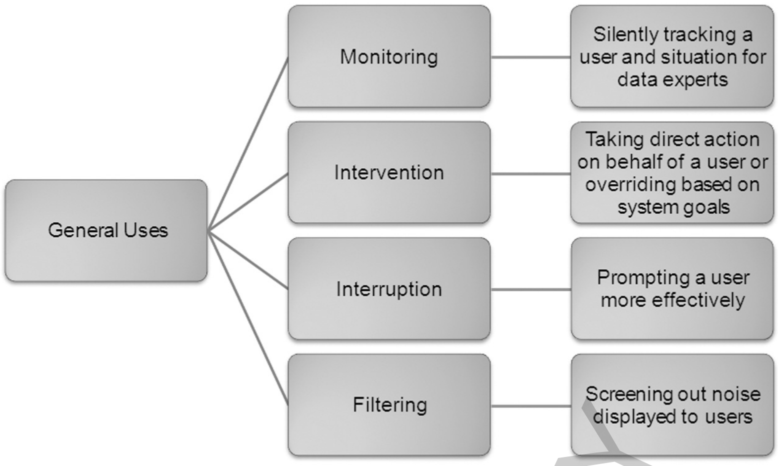

Fig. 4. General target applications and general uses for brain context.

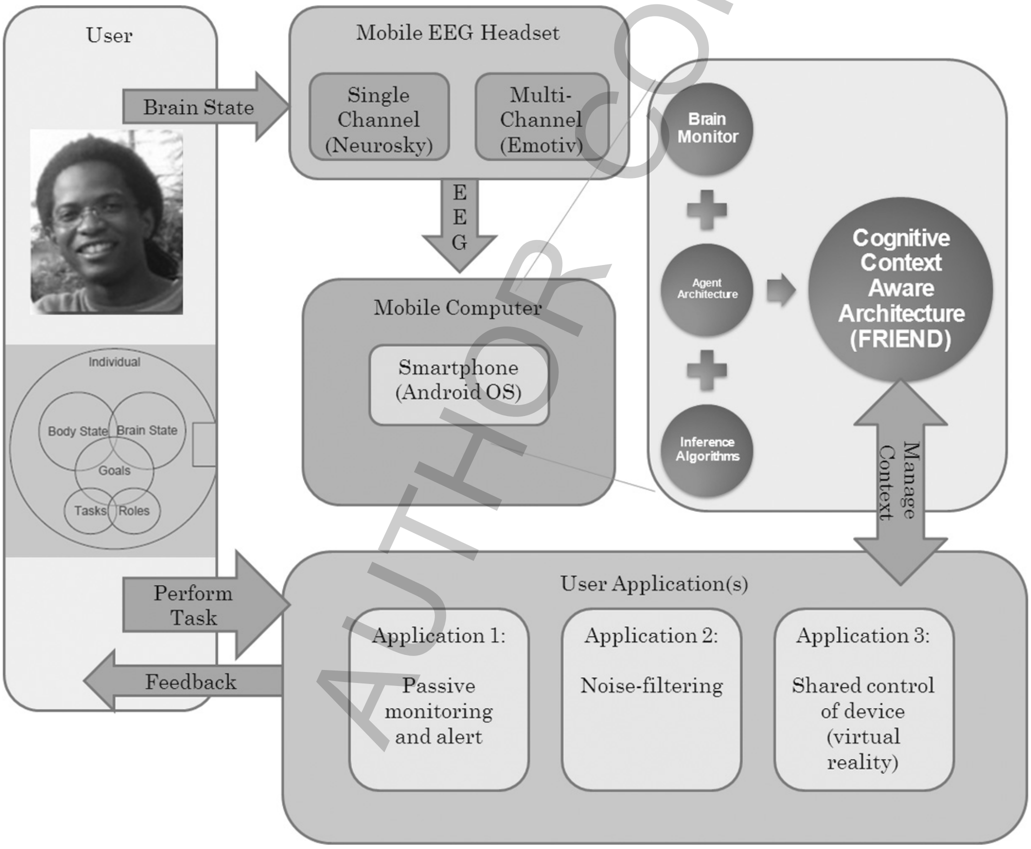

Fig. 5. An overview of the FRIEND brain context awareness agent system. A user of multiple applications has an intermediary to manage context.

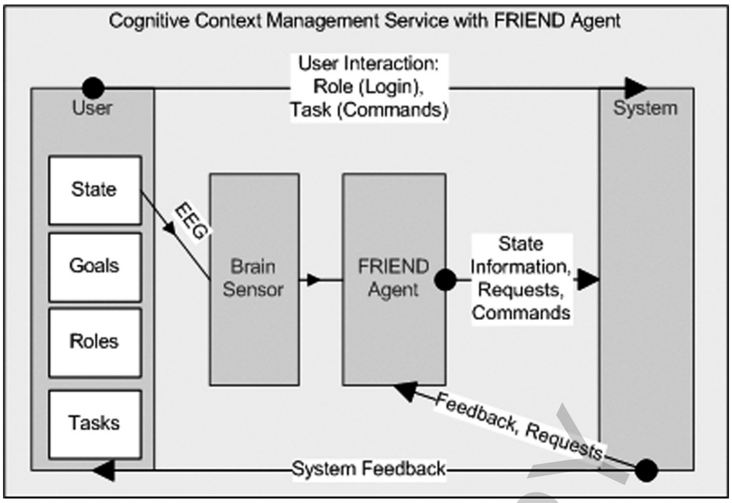

Fig. 6. FRIEND agents autonomously interface between a user and a system application, as a brain-context management service.

In terms of driving and shared control, there has been successful work on detecting driver's intention to brake before actions become observable [30]. Also, in [40], drowsy driving states were detected with EEG data. Both studies were on driving simulators. Finally, in [16], an architecture is proposed for a bodynet system for remote monitoring of EEG.

None of these representative approaches make use of hybrid soft-computing-agents for control or context management with brain data. This work proposes that these kinds of agents are a logical next step for work on EEG classification and targets this direction. The following section will discuss the proposed solution in more detail.

4. FRIEND: A unification of concepts towards brain-context in adaptive socio-technical systems

4.1. Overview

The FRIEND (Fuzzy Reactive Intelligent Everyday Neuro-sensing Device) architecture has been outlined in [48] and the architecture overview is seen in Figs 5 and 6. The framework consists of 1) a user, 2) a mobile EEG headset, 3) a mobile computer, 4) a FRIEND agent, and 5) an application or set of applications. The FRIEND agent performs brain-monitoring of the user in real-time, processing EEG signal data on a mobile platform, and uses this data to perform inferencing and make human-aware decisions for external applications. The combination of user state and situation state (obtained from applications registered with the agent beforehand) allow for the selection of plans which match both situation and application contexts. Effectively, the agent intermediary sends directives to existing applications that are already registered with the system. In this way the system as a whole becomes human-aware, without each application needing to specialize in brain context. Such a hybrid architecture enables the development of future socio-technical software systems that adapt to brain context.

4.2. Users of brain context management systems

Users are considered as having goals (for which they make use of an application) and performing tasks according to their roles. This information is largely available to existing systems, for instance, at

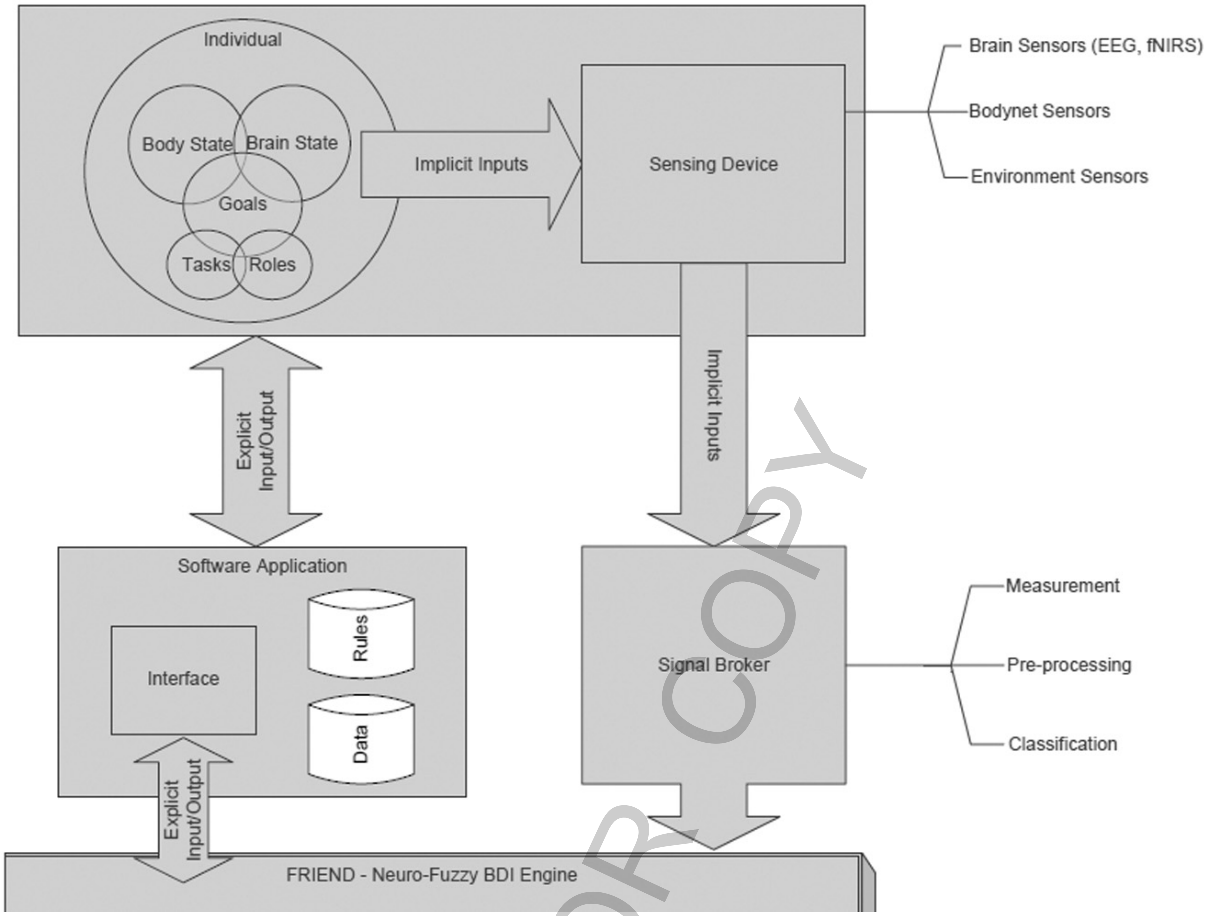

Fig. 7. The human-awareness agent cycle showing an individual performing explicit and implicit communication through the FRIEND architecture. See [48] for more details.

design-time a system is coded to handle specific roles via login, and enable certain tasks which may be performed by someone of that role. However, the state of body and mind of that user are rarely available to systems at either design or run-time. So users perform tasks and receive feedback from systems, but those systems cannot adapt to individual mental and physical contexts; the present state of human-machine interaction.

With the FRIEND medium, however, this is augmented with an agent intermediary to provide context related commands to systems. Figures 6 and 7 depict this new relationship.

4.3. Mobile EEG headset

A mobile EEG acquisition device is required and both the Neurosky Mindset [2], and the Emotiv EPOC [1] are targets for this system. The requirements for selecting a headset are that they be fast, portable, reliable, noise minimizing, commercially available, and simple to install and program. Both these headsets fit these requirements, with one key difference. The neurosky headset is a single channel device, while the other is a multi-channel device (12 channels).

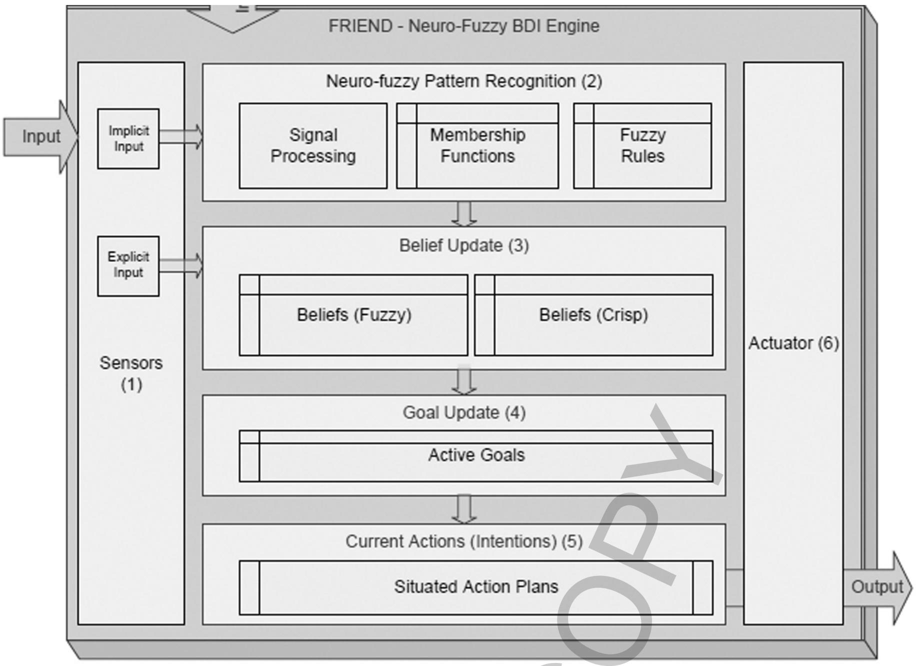

Fig. 8. The FRIEND architecture monitors incoming passive and explicit inputs, infers state based on signal data, fuzzy rules, and encoded knowledge models, before updating beliefs and selecting a response action on behalf of the user, depending on the system's active goals [48].

The single channel device will be used for the early settings of cognitive state estimation, providing for testing and development, (signal processing on a single channel is simpler). Also the device is inexpensive, providing access to features such as attention, meditation, and frequency band signals. However, the single channel device can only account for activity in the pre-frontal (forehead) region of the brain.

The multi-channel device will be used in later stages of the FRIEND project, where it will be useful to gain data for more features about the user. Its use of standard 10–20 positioning (coverage of multiple brain regions) [25] is an advantage, as different states are decipherable across different brain regions (e.g, prefrontal versus occipital regions when considering attention).

4.4. Mobile computing platform

In this work, a sufficiently powerful mobile platform is needed for 1) handling the agent architecture, 2) processing the brain information (and storage where needed), as well as 3) its communication with other applications needing brain context. Fortunately, the current generation of mobile phones have increased in processing power, and satisfy these requirements [56]. The Google Android operating system [4], is a target platform that provides a programming framework, for handling these as well. In the event that the platform is not powerful enough another mobile architecture may be used.

4.5. FRIEND agent: Initial architecture designs

Early work on the methodology for developing human-context-aware agents is seen in the Figs 7, 8 and 9, as taken from [48]. The agent architecture consists of sensors, a BDI interpreter, a neurofuzzy classifier, and a model of cognitive features as baselines. Using an internal neuro-fuzzy classifier, the

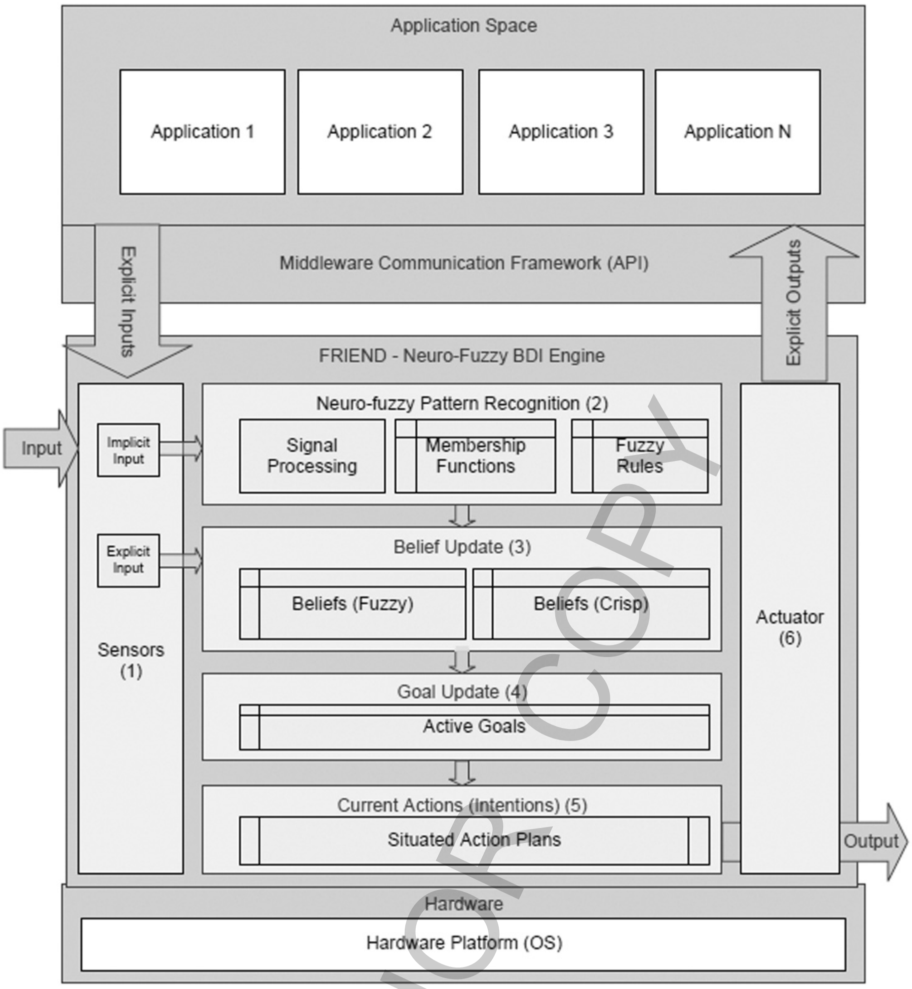

Fig. 9. The FRIEND architecture scenario expanded to the use of multiple applications [48].

agent is able to obtain and store classified state data as as beliefs about the user state within a standard BDI agent architecture, effectively combining explicit situation information and implicit user state information. In terms of implementation of the design, existing frameworks will be combined (using Python as the programming language, and the selected mobile computer platform). Table 1 shows an early selection of potential components and design tools. It is envisioned that the FRIEND architecture would prove useful for managing context for a single user of one or more applications, and also for future problems related to the sharing of contextual information between FRIEND agents, across different users and groups.

4.6. Application set

The FRIEND architecture is aimed towards servicing multiple applications with user brain context. This is seen in Fig. 9. In particular the applications are 1) Passive Monitoring, 2) Noise-Filtering, and 3) Shared Control.

Table 1
The programming tools in consideration for each module. Primarily the Python language is targetted for this work

Task module	Tools
EEG signal acquisition	Neurosky/Emotiv EPOC
EEG signal processing	Python PyEEG, NumPy, SciPy libraries
BDI agent	AgentFactory, with JPython support
BDI agent language	AgentSpeak via AgentFactory
Soft-computing (Neurofuzzy)	Peach (Python)
Middleware communication	AgentScape/Spade (Python)
Cognitive state gauges	Peach (Python soft-computing)
Mobile platform code	Google android (SL4A-Python environment)
Application 1: Passive monitoring	Custom app (Python)
Application 2: Noise filtering	Browser app (Python)
Application 3: Shared control	Second life app (Mixed)

4.6.1. Application 1: Passive-monitoring

This approach considers the FRIEND agent as a passive monitor tool for a manager of a team, such as a hospital nursing officer who must be aware of the state of her workers. It simply alerts whenever an individual (wearing a FRIEND agent) has a cognitive load level below a certain threshold. Such an application would be useful in practical situations to detect stress/load levels of employees, for instance. In this work, of course, the focus is more on the usefulness of the general agent than on the cognitive load metric.

4.6.2. Application 2: Noise-filtering

The Noise Filtering application is a general one that removes interface features (such as text sizes, or active windows), based on cognitive load. It has the job of either filtering information away from the screen if too noisy, i.e., the user is overloaded, as well as adding more information if the user is disengaged. This application represents a simple use of brain context that is also extensible to more important situations where concentration is crucial, such as driving on a highway.

4.6.3. Application 3: Shared-control

The Shared-control application makes use of brain context (cognitive load) to determine when to take over an object from the user. This is a relevant area of research in driving applications, where an intelligent vehicle can take over if its user is in a drowsy state, or is not paying attention to task, or is in an overloaded state. It is similar to the second application in this respect, but has the added condition that the device must return functionality to the user in an unobtrusive fashion. As such devices are not available this application will be simulated through the use of virtual software objects, such as in Second-Life [65], where in-world objects can be scripted. This has already been evidenced in [58], for interacting with Jason agents.

5. Conclusion

Agents for brain-monitoring are on the horizon, and the advancement of technologies makes this research timely. The use of the agent paradigm as a robust framework for autonomous control based on dynamic brain-context information is worthwhile for many situations. This technique aims at minimizing failures in systems due to human-factor issues by improving and streamlining technologies to social context. This fosters improved adaptability in systems, effectively becoming human-context-aware systems (specifically brain-context-management systems). This proposed work contributes to the development of such systems by outlining the central motivations, literature, and a path towards such systems, presenting an early architecture design (FRIEND) and proposed experimental applications. Future work will advance with implementations of these designs, and experimental applications of high-functioning, and practical brain-monitoring agent assistants.

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Authors' Bios

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