Electroencephalograms for Ubiquitous Robotic Systems

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Abstract

Ubiquitous robotics augments the capabilities of one or more robots by leveraging ubiquitous computational and/or sensorial resources. Augmentation complements and/or enhances the capabilities of one or more robots while such robots can simultaneously serve as intermediaries to ubiquitous services. Electroencephalograms (EEG) are Brain-Computer Interfaces that consist of a series of conductors placed on the scalp. These conductors measure voltage fluctuations in the brain, and using machine learning techniques can be classified and used to command ubiquitous robotic systems. The purpose of our work is to increase the collaboration between humans and surrounding robotic components while fulfilling a certain goal or requirement. We aim to do that by granting humans more precise manipulation, (i.e., brain-driven), over part or all of the involved robotic components. This paper presents our approach on the integration and benefits of an EEG interface within ubiquitous robotic systems.

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1. Introduction

\textit{Ubiquitous Computing} (UC) is a model of \textit{Human-Computer Interaction} (HCI) within which computational resources are available through everyday objects. A user can have tasks carried out simultaneously on the surrounding objects without their awareness. \textit{Ubiquitous Robotics} (UR) is a model of \textit{Human-Robot Interaction} (HRI) within which robots harness the pervasive computational resources of UC in order to complement or enhance their functionality. \textit{Brain-Computer Interfaces} (BCIs) allow for asynchronous communication between the brain and a computer \textit{Electroencephalograms} (EEGs) are a noninvasive form of BCI. EEGs consist of a series of conductors placed on the scalp to measure discrete voltage fluctuations across the brain. These fluctuations are then applied to machine learning algorithms to classify brain activity, which can then be used to control a computer.

EEGs present a number of benefits over classical HCIs, especially, but not exclusive to assistive tools for the disabled, providing a noninvasive means of communication. EEGs allow for the transmission of actions wirelessly while allowing the user to perform other tasks, removing the need for buttons, vocal commands

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or gestures. In addition to this, EEGs allow for the detection of facial expressions and blinking, even before the user has made them. EEGs also allow for the transmission of emotional states, such as fatigue, focus and happiness. And with recent advances wireless EEGs headsets present a cost effective BCI.

This paper presents the application of EEGs headsets to the area of UR with a series of scenarios including **UR Service Activation**, **UR Emotional State Adaption**, **UR User Satisfaction Detection** and **UR Emergency Medical Intervention**.

2. Related Work

*Ubiquitous Computing (UC)* is a method of enhancing *Human-Computer Interfaces (HCIs)* by making many computers available throughout the physical environment, but making them effectively invisible to the user. The notion of UC first came to the forefront with a 1991 Scientific American article by Mark Weiser called "The Computer for the 21st Century" [1]. [1] presented the notion of computation weaving its way into daily life until it becomes indistinguishable. The seminal work of [1], paved the way for a broad spectrum of computer science problems [2], associated with hardware components, network protocols, interaction substrates, applications, privacy and computational methods. Many authors capitalized on the outstanding issues presented in [2] and experimental intelligent environments started to appear in order to confront those issues. *The EasyLiving Project* [3] undertaken by Microsoft looked to develop the underlying architecture and technologies. The focus of [3] being to aggregate diverse devices into a coherent user experience. The result garnered advances in middleware, geometric world modelling, perception and service description. The work of [4] introduces the notion of cooperative buildings and *roomware*, including an interactive electronic wall, table, augmented chairs, with each of these also having virtual representations for multi-modal interactions. After the introduction of multiple approaches, [5] proposed a common model, stating that it would be more effective from an economic and scientific perspective. This model proposed levels of abstraction in regards to embedded and mobile devices, with a focus on distributed, collective and cooperative perception systems.

There are many examples of *SW* being used in UC middlewares, one of which is [6]. [6] propose a *Ubiquitous Semantic Space (USS)*, in an effort to provide a common solution to both communication and context-awareness in UC, resulting in a middleware framework. [6] use OWL [7] to describe services, then describe system behaviors using the *Semantic Web Rule Language (SWRL)* [8]. These SWRL [8] behaviors are then executed using the JESS reasoner engine. Similarly, [9] propose a semantic location-aware model, again using OWL [7], SWRL [8] and the JESS reasoner. Entities like users, devices, service providers and computing agents are included in the model. With this model and with the use of JESS specifically, the location of users can be inferred. With the use of semantic web technology providing a robust method for service composition and execution, some started to investigate *Quality of Service (QoS)* models. Citing the mobile and resource-constrained nature of ubiquitous computing being the incentive, [10] propose their own hierarchical model. With the addition of a QoS model, context reasoning can be improved, guiding the selection of services with higher reliability. They do this through first-order and fuzzy logic evaluation, along with quantitative methods to quantify the quality factors. Similarly, [11] propose their own QoS model, while using OWL [7] for service description, they diverge from the status-quo with a genetic algorithm-based optimization for service selection.

While [12][13][14][15][16][17] focused on the integration of robotic systems with sensor networks, proceeding work focused on fusing distributed sensor data, as well as the dynamic integration and removal of sensing/actuation elements. The work of [18] proposes a distributed multiagent system also consisting of intelligent sensors and actuators distributed both onboard robots and throughout the environment. The robots, sensors and actuators are handled by real-time software agents which exchange information on a distributed blackboard. Three different software agents are presented, *simple reflex agents*, *agents that keep track of the world*, and *goal-based agents*.

Identically to UC, approaches to UR have been developed using SW technologies. [19] introduce the *Ubiquitous Robotic Companion (URC)*, or specifically the service framework supporting it, called *Service-oriented Ubiquitous Robotic Framework (SURF)*. [19] claim that SURF allows for automated integration of networked robots into UC environments using SW. As with [6][9] in UC environments, system knowledge
Brain-Computer Interfaces (BCIs) have been studied during the previous decade as a means of providing HCIs for the disabled. BCIs provide a means to classify brain activity, instead of peripheral muscle movements, to control computer applications. The Electroencephalograph (EEG) is used to measure electrical activity along the scalp. Consists of a series of strategically placed electrical conductors. Through these conductors measurements are taken of the voltage fluctuations from neurons in the brain. Using machine learning classification techniques, specific brain activity can be recognised and harnessed for thought recognition, emotional state, fatigue, sleep disorder, coma, tumors and stroke diagnosis. [23] reviews a number of applications areas for BCIs, aside from EEGs. [23] stresses the importance of BCIs as a means to provide rich information on the user’s state, potentially providing personal mental information such as task engagement, cognitive workload, surprise, satisfaction or even frustration. [23] continues by stating that this information could be used to design context sensitive systems that adapt themselves for optimal user support, the connection between this and UR is clear. [23] presents a schematic of BCI components, adapted and included in Figure 2.

Classical BCIs provide detailed, single-neuron activity from microelectrodes implanted in the brain [24]. The use of invasive techniques allows for direct connection to the motor, premotor, and posterior parietal
cortex to allow for classification of hand and arm movements reliably. However, in a domestic or research setting the invasive method is not preferable due to health risks and ethical implications, and it is for these reasons EEGs are preferable.

Within the area of robotics, the focus of EEGs has been for the control of aids for the disabled. The standard application developed has been an electric wheelchair [25] [26]. [26] states that EEGs have been determined to be too slow for fine/rapid actuation tasks, however they present a system that allows the navigation of a robot between rooms with a performance comparable to manual control. [25] also presents a system applied to a wheelchair in the same year. Other examples of EEGs in concert with robotics include wheeled, quadruped [27], bi-pedal [28], quadrotor and medical [29].

The work of [23], first suggested the notion of EEGs being incorporated into intelligent spaces. The incorporation of EEGs into UC environments have created a series of challenges, as outlined in [30]. Those challenges lie in the development of mobile and user-friendly devices, which are entirely wearable and noninvasive. In addition this, the automation of processing techniques for the rapid learning of brain patterns and their transmission. [30] maintains that the inclusion of EEGs in UC environments as a promising method to obtain information, and express an interest of pursuing this further with the development of data fusion methods for electromyograms (EMGs), electrocardiograms and EEGs. [30] have also expressed an interest in exploring the role of EEGs in daily life. Finally, the work of [31] describes using EEGs a security tool within UC environments, one which could be used in place of fingerprint or iris solutions.

3. Applications

The use of EEGs within UR provides many interesting research opportunities. In addition with the introduction of consumer-level EEG headsets the possibility of practical application to domestic, industrial and commercial settings is a reality. One such consumer-level headset is the Emotiv EPOC, a high resolution, multi-channel, wireless neuroheadset. The Emotiv EPOC uses a set of 14 conductors placed over the prefrontal cortex to allow the detection of thoughts, emotions and facial expressions in real-time. In addition to this, the Emotive EPOC includes a gyroscope to measure the users head orientation and motion. In this section, a number of UR applications utilizing the Emotiv EPOC’s functionality are proposed. They are Service Activation, Service Emotion Adaption, Reinforcement Learning & QoS Evaluation, Medical Emergency Intervention and User Identification.

3.1. Service Activation

Within UR, the activation of services is usually performed via a manual interface, like a PC, tablet or phone. More intuitive approaches using voice control or gestures have also been proposed. With an EEG headset it is possible to go right to the source of the activation command, the brain. With an EEG headset, the user has the freedom to perform other bodily functions, as well as converse freely while also activating UR services.

Figure 3.1, describes the action flow from the brain to the UR services within a hypothetical UR system. Initially, the user has trained the BCI to classify 4 thought patterns. When the user focuses on a prelearned state of mind, the neural signals are read by the EEG headset. Signals from the EEG headset are then passed wirelessly to the pattern classification software of the BCI, running on a central system. After classification, the signal is represented using the associated UR middleware and onto the Service Ontology. The associated service is then selected, at which time the service orientated subsystems, such as discovery and planning, compose the intended service, after which it is carried out by the UR system. The user will know if the intention was correctly registered through the apparent activation of the service and whatever form it might take.

In order to illustrate this concept further, the following scenario is presented. A user is bedridden and would like a refreshment from the kitchen. The user has a number of trained services for their EEG headset. They are, 1) request the presence of a Turtlebot, 2) request the presence of another Turtlebot 3) actuation of the curtains and 4) turning on/off of the bedroom light switch. The user first requests the presence of a Turtlebot, using wireless arbitrary sensors throughout the home, the Turtlebot locates the user in their
bedroom. Using path-finding tools, the Turtlebot will travel to the bedroom, once there scan the room for the user using facial recognition, once found will move to within arms reach of the user. The user then uses a manual interface on the Turtlebot as well as its display actuate a second Turtlebot to acquire a can of soda. Using the second trained behavior, the user requests the presence of the second Turtlebot, with can of soda in tow. While waiting for the second Turtlebot to arrive, the user commands the actuation of the curtains and turns off the lights in the bedroom, both of which are done so by localising the user to a specific room, allowing for flexibility of trained commands to be location specific. The work of [9] mentions the need for user context-data, and shaping services around location data.

While the previous scenario featured thought-based activation, the Emotiv EPOC will also detect facial expressions and blinking. This opens the possibility of either extending the number of available UR services to activate, or rely solely on facial expression or blinking to activate the UR services.

3.2. Emotion Adaption

As stated previously from [23], BCIs provide a means to design context sensitive systems that adapt themselves for optimal user support. In order for a UR system to passively recognise the mood of a user, it relies on external visual systems and facial recognition software. This approach is constrained by the orientation of the user to the camera and lighting levels. In addition this, some emotional states are not even registered facially. The Emotiv EPOC unit has the functionality to detect the users emotional state, even to detect facial expressions before the user makes them. This opens up the emotional state of the user in a reliable way, for the UR system to then react in an appropriate way.

Figure 3.2 depicts an expansion over the previously proposed action flow of Figure 2. Figure 3 now includes a contingency for an emotion specific UR service domain, with a distinct UR service domain for thought directed actions. The has trained the BCI to classify 3 thought patterns, the action flow of which is mirrored with that of the Service Activation described previously. When the message has reached the Service Ontology module, there is a divergence, with only a set of 3 UR services available to perform. The associated thought-based service is selected, and the service is carried out by the UR system. While there is a now a Thought Activation domain, there is also a Emotion Activation domain also. This domain is responsible solely for carrying out UR services corresponding to the users emotional state, these are intended to be passive UR services.
As with the previous section, to illustrate this concept further, a scenario is presented. The UR has two behaviors in place for the emotional state of a user. The first is for anger, the second is for fatigue. In the first scenario, the user has received a phone call, and has received news that has greatly angered them. The angry state of mind is registered and passed on the UR system. Using this context-data the system moves to perform the appropriate predefined action. In this case, that action is for the immediate return of all mobile robots to their charging stations. If return is not possible, due to the user as an obstruction, find an empty room and wait. These actions are performed to ensure not only the safety of the robots in the UR system, but also that of the user. In addition to the robot maneuvers, soothing classical music is now played throughout the user’s home.

3.3. User Confirmation and Evaluating QoS

Some UR systems consist of learning functionality, adapting themselves to the habits of the user. The work of Project RUBICON [32] features self-sustaining and learning solutions. An outstanding issue of [32] has been the need of a confirmation signal to the ecology to bootstrap the wirelessly distributed reinforcement learning for autonomous service selection. An EEG headset could provide a binary feedback to the ecology, trained on a brain pattern the user knows to perform when the ecology performs sufficient or not. This would provide a passive interface to the ecology, removing the need for a button, or vocal cue. The EasyLiving Project [3], describes the reliance on having badges, cameras or buttons in order to get context from users. The work of [33] describes sensing context information and providing personalised services according to current context and user’s requirements as a crucial issue.

Figure 3.3 depicts an addition to the Project RUBICON architecture, which now includes a BCI on the Sensing and Actuation Layer. On the execution of a service within the RUBICON system, the failure of success of a service, as in its mechanical success, is fed into the Learning Layer, as a training signal to be associated with the same service execution strategy. The Learning Layer then informs the Control Layer and Cognitive Layer on service execution strategies in the future. The role of the BCI component is to enhance the Sensing and Actuation Layer to encompass the user’s emotional response to service execution strategies.

In order to illustrate the role of BCI-based user confirmation, the following scenario is presented. The BCI component has been configured to recognise frustration in the user. The user returns home during
Fig. 4. Schematic of the proposed role of a BCI within Project RUBICON

the night, as routine, the user moves through the house and turns on the lights. The Cognitive Layer of the RUBICON system detects the novelty and repetition of this behavior, and decides to intervene the next night by turning on the lights. The next night, the user returns and finds that the lights are turning on as they move through the house, however they unceremoniously turn off 10 minutes later. The user wearing the EEG headset feels frustration at having to now move through the house to turn back on the lights. The user’s frustration is registered by the central BCI component, which is linked to the Sensing and Actuation Layer of the RUBICON system, which then passes the negative signal to the Learning Layer. The next night, the lights stay on for a longer period of time.

The previously mentioned BCI confirmation signal, serves as one aspect of describing QoS in a UR system. The work of [10], proposes the need for a QoS model within UC. The related work of [22], proposes a QoS model for UR based on arbitrary metrics, extension of this work to include confirmation of QoS from the user could close the loop.

Another issue within UR systems is getting a confirmation of attention from the user. In situations where the user is approached by a robot and presented with information, in order for the UR system to know that the user has paid attention, a confirmation signal could be set for that scenario. This would remove the need for voice recognition, or manual confirmation. If this was combined with face tracking, a robust method for user perception could be established. Work on the area of attention recognition with EEGs has been investigated by [34].

3.4. Medical Intervention

The work of [35] points to the ability of EEGs to predict the onset of seizures, specifically performing time series analysis on the EEG dynamics to search for similar patterns prior to an event. Directly connected to UC, [30] have proposed a system called Online Predictive Tools for Intervention in Mental Illness (OP-TIMI). The role of a ubiquitous robotic system could be as simple as notifying the emergency services and opening the door to allow them entry to the premises, to act on the individual to place them in a recovery position, conversely the protection of the user by removing the robots from the environment while the person has an event.

The detection of such brain activity may very well be beyond the capabilities of the Emotiv EPOC headset, and only be feasible with a medical-level EEG.

3.5. User Identification

The idea of identifying users in a ubiquitous robotic space by using just the headset. Using their brain patterns as a means to describe the user. The work of [31] describes using EEGs as a security tool within UC environments, one which could be used in place of fingerprint or iris solutions. The headset being WIFI enabled, in addition to having accelerometers, could provide a ubiquitous robotic system with invaluable
information about the users location within the environment. Such information would also for the system to adapt the availability of services depend on their location, possibly deactivating unnecessary services in other locations to be more power efficient.

4. Conclusions & Future Work

In this paper, a new mode of interaction with UR systems is introduced, which the user of EEGs. A series of proposals for integration with current UR models are presented. The first being Service Activation, replacing the need for manual interfaces, like a PC, tablet or phone. In addition, eliminates the need for voice recognition tools, and gesture recognition. Allowing the user the freedom to perform other tasks unencumbered. The second being Emotional Adaption, allowing UR systems to adapt to the mood of the user, carrying out services that can elevate negative emotions or fatigue, in an attempt at maintaining comfort. The third being User Confirmation, again replacing the need for manual interfaces, but focused on establishing the users preferences in regards to the UR services. Finally, Emergency Medical Assistance, allowing for home monitoring of a user susceptible to brain related medical issues, such as a disposition to seizures. Allowing a UR system to come to the assistance of the user in an emergency.

Under consideration for future work, is the exploration of each of the above integration and benefits of EEGs within UR systems. Developing the architecture to support EEGs within a dynamic UR testbed.

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