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Incorporating Human Intention into Self-Adaptive Systems

Shihong Huang, Pedro Miranda
Computer & Electrical Engineering and Computer Science
Florida Atlantic University
Boca Raton, FL 33431, USA
shihong@fau.edu, pmirand1@fau.edu

Abstract—**Self-adaptive systems are fed with contextual information from the environments in which the systems operate, from within themselves, and from the users. Traditional self-adaptive systems research has focused on inputs of systems performance, resources, exception, and error recovery that drive systems' reaction to their environments. The intelligent ability of these self-adaptive systems is impoverished without knowledge of a user's covert attention (thoughts, emotions, feelings). As a result, it is difficult to build effective systems that anticipate and react to users' needs as projected by covert behavior. This paper presents the preliminary research results on capturing users' intention through neural input, and in reaction, commanding actions from software systems (e.g., load an application) based on human intention. Further, systems can self-adapt and refine their behaviors driven by such human covert behavior. The long-term research goal is to incorporate and synergize human neural input. Thus establishing software systems with a self-adaptive capability to "feel" and "anticipate" users intentions and put the human in the loop.**

Index Terms—**Brain computer interface (BCI), human computer interface (HCI), neural input, self-adaptive systems, overt and covert behavior, human in the loop**

I. INTRODUCTION

In 2008 IBM started the "Smarter Planet" [8] initiative that emphasized that systems and industries are becoming more instrumented, interconnected, and intelligent. Smart cities, smart transportation, smart energy & utilities, smart infrastructures, and smart homes—these "smart" systems are the representatives of complex and dynamic software intensive systems. These attributes require the systems to be able to adapt themselves at runtime to react and deal with the uncertainties and unpredictable nature of the environments in which they operate (e.g., intrusions, faults, and exceptions). In general, uncertainty may be due to changes in the operational environment, variability of resources, and new user needs. As Garlan [2] [3] posited, human behavior contributes large amounts of uncertainty, and if we add *covert* human behavior (e.g., intentions, desired actions, attention, thoughts, memories, or emotions) even more uncertainty will result.

In today's smart environment, users and systems are intimately involved. As technology becomes more ubiquitous and software becomes more task-oriented, the self-adaptive capability requires the system to be able to modify its behavior and/or structure in response to its perception of the environment, the system itself as well as its goals [14] with minimal complex manual interaction. In the self-adaptation world, such systems are sometimes referred to as "mixed initiative" systems where users and systems work together to accomplish certain goals.

The advancement of neural science and brain computer interfaces (BCI) [15] enable software systems to incorporate the mental states of its users and covert attention into the perceived environments and systems goals. On the frontier technological enablers are arrays of sensors that can convey information about brain states. The most widespread technology electroencephalography (EEG) devices (device that is used to measure ionic current flows of the brain's neurons in order to understand brain functions) have recently evolved from specialized equipment reserved for neuroscientists to more general gadget accessible to ordinary users (see section II.A).

Traditional self-adaptive systems research has focused on inputs of systems performance, resources, exception, and error recovery that drive systems' reaction to their environments [7]. One of the missing links in the many existing self-* properties of self-adaptive systems is to address how to anticipate and react to humans' thoughts and mental states. This can be accomplished through neural inputs. The intelligent ability of these self-adaptive systems is impoverished without knowledge of a user's covert attention. As a result, it is a challenge to build effective systems that anticipate and react to users' needs as projected by covert behavior.

This paper continues our existing research collaboration on brain computer interface [13][9] and exploiting the synergy between software systems and neural inputs [18]. We present our preliminary research results of creating a brain mouse to command actions of a software system (e.g., load an application) based on human intention. Further, systems can prepare resources by self-adapting to human intention. The long-term research goal is to incorporate and synergize human metal state to establish software systems with a self-adaptive capability to "feel" and "anticipate" users intentions, and put the human in the loop [6]. This is a paradigm shift of software systems from react to anticipate.

The rest of this paper is organized as follows. Section 2 describes enabling technologies and BCI that decipher neural input. Section 3 describes our research methodology of capturing human intention by using the covert behavior input to self-adaptive systems. Section 4 illustrates our preliminary results of implementing such methodology. Finally, Section 5 concludes the paper and outlines avenues for research.

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II. ENABLING TECHNOLOGIES

Brain Computer Interface (BCI)'s goal is to connect computer actions with neural input signals indicating the user's intentions, desired actions, covert attention, thoughts, memories, and covert emotions etc. BCI systems minimally contain a sensing equipment to measure brain activity, an "interpreter" or "classifier" to link the measured brain activity with specific brain states (e.g. pattern recognition algorithm, support vector machine, ICA/PCA, artificial neural network, etc.), and an output that changes the state of the computer system or its appendage according to the rules of the BCI. Usually, the BCI functions in a closed loop, which describes that the agent whose brain activity is used by the BCI is made aware of the changes that happened as a result of his/her/its brain activity [18]. The main enabling technologies used in this research are Electroencephalography (EEG), P300 potential, and Steady State Visually Evoked Potentials (SSVEP). These technologies are described briefly below.

A. EEG

Electroencephalography (EEG) is the most common BCI enabling technology, which measures ionic current flows in the brain's neurons over the course of brain functions. This technique recently evolved from specialized equipment reserved for neuroscientists to more accessible gadgets for ordinary users [18]. This move was made possible by innovations that evolved from "wet" electrodes operated with conductive gel, expensive hardware, high-end bioamplifiers and high-density wiring, to consumer-use EEGs that use dry electrodes and wearable headsets with lightly-wired or wireless transmission of brain signals [5][1][20][16].

B. P300

The P300 potential is elicited by rare, task-relevant event and is often recorded in the EEG signal at a latency of approximately 300 milliseconds after the presented stimuli, an "oddball" paradigm [4]. The stimulus can be visual, auditory, or somatosensory which results in a positive peak impulse with a duration of 150-200 milliseconds in the EEG signal [17]. To detect the P300 signal, typically a 10-20 electrode configuration is used.

C. Steady State Visually Evoked Potentials (SSVEP)

The Steady State Visually Evoked Potentials (SSVEP) is a visual stimulus that results in a stable voltage osculation based on the sinusoidal frequency of the object that retains a human gaze. SSVEP is a direct response in the primary visual cortex and an indirect cortical response via cortical-loops from the peripheral retina, while a cognitive task is performed [17]. The SSVEP signal is a frequency that is generated in the brain by gazing at an object that is flashing at a specific frequency, an example of this would be an icon on a computer screen flashing at 60Hz. The SSVEP visual stimulus has a range from 3.5Hz to 70Hz and can be measured using 10-20 electrodes [11][4][17].

III. RESEARCH METHODOLOGY

A. Brain Inspired Self-Adaptive Systems

In their seminal paper on the vision of autonomic computing, Kephart and Chess [10] indicated that an autonomic structure typically consists of one or more managed elements coupled with a single autonomic manager that controls and represents them. When taking neural input and human covert behavior into consideration, the classic MAPE-K elements can be mapped into the corresponding brain states processing activities (sensory systems, cognition, (frontal) executive functions, and motor behavior) all controlled by neural feedback loop. The mapping is shown in Fig. 1.

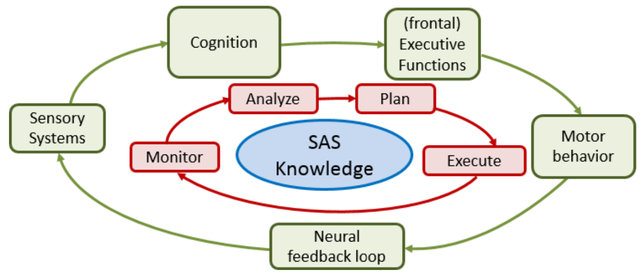

Fig. 1: Map Brain States to Autonomic Element Structure

Our mission is to integrate neural input and human covert behavior into a self-adaptive system in such a way that computer resources can be accurately pre-allocated before the user performs a specific action based on resource history and previously acquired EEG signal analysis. The system will adapt to user's intention based on an evaluation of actions performed in the past to determine which resources to allocate. The self-adaptive systems will then use a pattern analysis algorithm to re-evaluate the new results after the predicted action is performed in order to refine future resource allocations. We have designed and partially implemented a prototype to show the feasibility of incorporating human mental state into software systems. Particularly, as a first step, we are able to control a software application on a computer screen by a brain mouse (covert attention). The next sections describe the system design and preliminary results.

B. Brain Mouse Design

The concept of the BCI device is developing a computer add-on that is event related; mimicking the actions of a mouse or a touch screen to load an application. The device interfaces with the computer just as a mouse or keyboard would, but instead of using the overt behavior (physical mouse click), the system uses covert behavior (intention) signals obtained from brain signals [19]. The approach uses a hybrid BCI system [4].

The Adaptive System Circuit includes a computer application used to generate the stimulus and to communicate with a DSP. The application performs actions similar to the functions of a mouse and is shown at z-plane zero on every screen (cf. Fig. 2). The red rectangles on screen identify the stimulus that controls the x/y coordinates of the mouse cursor on the screen. The green square indicates the left click command.

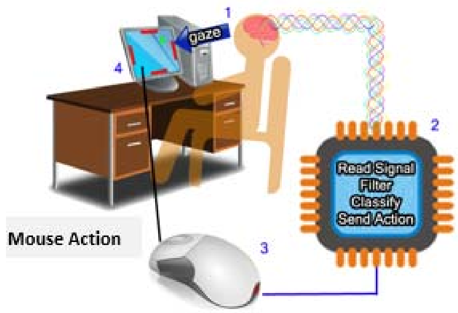

Fig. 2: Adaptive System Circuit. Part 1: User gazes at a specific stimulus on the computer screen. Part 2: DSP processes the EEG signals to identify an event in the user's brain. Part 3: DSP translates the EEG event into a mouse event. Part 4: Computer performs the mouse event.

The hybrid system signals used in the experiment include the P300 stimulus and the Steady State Visually Evoked Potentials (SSVEP). The SSVEP controls the coordinates of the mouse, by placing four rectangles at the edges of the computer screen (cf. Fig. 3). Each of these rectangles will flash at a unique frequency in the range of 6-20Hz. The range is in the lower band of frequencies that can be found by analyzing the SSVEP. This is the ideal range due to less interference from exterior components. Some of the components that can interfere with the EEG signals at higher frequencies are EMG (40-64Hz) or power line hum (50/60Hz) [11]. By analyzing the signals coming from the brain, the DSP is able to capture the SSVEP osculation frequency and identify which rectangle the user is focused on.

The DSP notifies the computer to move the mouse cursor towards the rectangle flashing at the SSVEP frequency. The mouse continues to be move towards the specific rectangle until focus is removed from that rectangle. If the user's focus moves to another rectangle the cursor moves towards the newly focused rectangle. Once the absence of focus on all four rectangles has been detected the system acknowledges that the user has placed the mouse in the desired click location.

The system then begins to flash a square that is filled with one of four different colors and letters. The first color is yellow with the letter "DL" which identifies a mouse double left click, the second color is green with the letter "L" identifying a left mouse click, and the next color to fill the rectangle will be blue with the letter "R" identifying a right mouse click. The last color displayed is white with the letter "N" identifying no mouse click. Each of these colors are displayed on the screen for approximately one second and in the meantime the DSP is searching for the P300 event. Upon the detection of a P300 event the DSP sends a command to the computer to perform the double left, left, right, or no click at the current location of the mouse.

Fig. 3: Screen Stimulus Setup. The red rectangles represent the mouse location stimulus. The Yellow, green, blue, and white squares represent the double left, left, right and no mouse click event stimulus.

The process of a mouse click is as follows. First, the application generates the SSVEP stimulus to identify the desired location of the mouse cursor and sends a signal to the DSP to search for the SSVEP signals. Once the DSP has determined that the user is not focused on any of the four rectangles it sends a signal to the computer application to generate the mouse click stimulus. In turn the computer application begins displaying the different mouse events and sends the currently displayed event to the DSP. Once the DSP identifies the P300 event, it sends a signal to the computer to perform the specific action. Upon completing the action the system restarts the mouse location identification process again.

IV. PRELIMINARY RESULTS

In this project we collaborate with a neuroscientist, Dr. Tognoli and her research group [9][19]. They have developed a BCI prototype based on covert attentional shifts [13]. We exploit the neuromarker ξ that arises in the brain when users seek information in the periphery of the visual field. We have successfully been able to move a car on the screen by detecting the neuromarker ξ. Our ongoing research aims to decode the position of the user's focus of attention from brain signals. This information opens up possibilities to develop a computer system endowed with predictive capabilities. It provides contingencies for future actions that the user is likely to undertake in the next 0.25-3.0s. Accordingly, it could be used to pre-emptively pre-allocate computer resources and background tasks to fulfill the user's intended action [19].

As an intermediate step before fully decoding the position of user's focus on the screen by using neuromarker ξ, the EEG signal acquisition device is setup using 10-20 Ag|AgCl electrodes which provide the best performance in EEG applications [12]. The electrodes are connected to the analog-to-digital converter inputs of the TI ADS1299 EEG analog chip which is a chip designed specifically for EEG applications. The ADS1299 is connected a TI TMS320C5515 Digital Signal Processor (DSP). The DSP reads the digital signals from the ADS1299, filters, processes, and classifies EEG signals as mouse events either to move (left, right, up, down), double left click, left click, right click, or no click. The

DSP sends the command to the computer to perform the desired action. The input is similar to the PhysioNet waveform as shown in Fig. 4.

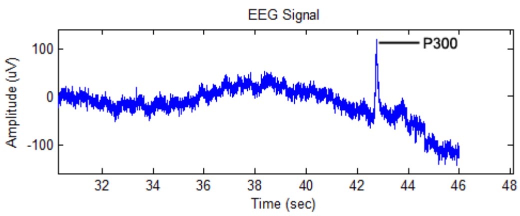

Fig. 4: EEG P300 impulse signal processed in MATLab. The P300 impulse width is approximately 200 (ms) and has amplitude of 120 (uV).

V. CONCLUSION AND FUTURE WORK

This paper intends to challenge the software engineering community by incorporating human intention in self adaptive systems. Keeping humans covert behavior in the loop and directly connect brain neural input to software systems is an inevitable phenomenon that the software engineering community should embrace. Human covert behavior can provide the system with knowledge about users' mental states, such as user's intention. This paper presents two BCI approaches, i.e. SSVEP and P300 EEG stimulus signals. Furthermore the methodology for a device that replaces the overt behavior necessary to control a mouse on the computer screen has been replaced by the covert actions using brain stimulation of a hybrid BCI system that includes the SSVEP and P300 EEG events.

For the future work we will evaluate the benefits of replacing the P300 stimulus with the SSVEP stimulus to control mouse clicks. The potential benefit is to optimize the performance of the mouse click. In an effort to continue to move towards the overall goal of this research, we will add into our implementation the neuromarker ξ, which is discovered by our collaborator Dr. Tognoli. The purpose of ξ will be to determine when the user wants to make a change in their current working environment. For example, if they want to click on a new program or scroll down on the current document they are reading. ξ will be used as a trigger to start scanning for the SSVEP signals. The long-term research goal is to incorporate and synergize neural input to establish software systems with a self-adaptive capability to "feel" and "anticipate" users intentions, and put the human in the loop.

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