Gaze-Directed Ubiquitous Interaction Using a Brain-Computer Interface

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ABSTRACT

n this paper, we present a first proof-of-concept for using a mobile Brain-Computer Interface (BCI) coupled to a wearable computer as an ambient input device for a ubiquitous computing service. BCI devices, such as electroencephalogram (EEG) based BCI, can be used as a novel form of human-computer interaction device. A user can log into a nearby computer terminal by looking at its screen. This feature is enabled by detecting a user's gaze through the analysis of the brain's response to visually evoked patterns. We present the experimental setup and discuss opportunities and limitations of the technique.

Keywords

Brain computer interface, gaze tracking, electroencephalogram, biometrics, object selection, authentication.

Categories and Subject Descriptors

H.5.2 [**Information Interfaces and Presentation**]: User Interfaces; K.6.5 [**Management of Computing and Information Systems**]: Security and Protection—*Authentication*

Keywords

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1. INTRODUCTION

As suggested in [4], brain-computer interface (BCI) technology can become a useful device for human-computer interaction. BCI is able to capture ambient properties of human activity rather than requiring active operation. This is not only useful for assistive technology, but also allows input for a computer system to be gathered without inducing cognitive load on the user. It is therefore suitable for contextual computing, such as activity recognition. We suggest the integration of BCI into the toolset of user interface designers, assuming that BCI will soon become sufficiently accessible and inexpensive.

In this paper, an electroencephalogram (EEG) based BCI is used to capture brain activity with a wearable computer. Unlike typical laboratory experiments, this wearable hardware setup allows a user's brain activities to be monitored whilst freely roaming an environment. The wearable device therefore enables the prototyping of ubiquitous computing services based on BCI.

To illustrate the potential of mobile BCI as an input device, we have created a system for secure login to a computer terminal within visual proximity of the user by detection of characteristic brain patterns evoked when looking at a blinking screen of the computer terminal. A proof-of-concept implementation of this type of interaction using a real world, secure remote desktop software was implemented. We present first experiences how to build and operate a ubiquitous computing system involving BCI as a personal input modality. While our approach does not yet fully qualify as biometric identification in the sense that a user's identity is uniquely verified through physical means, it does provide the verification of the presence of a digitally authorized user at a particular task location, and has potential to be upgraded to a full biometric identification system with enhanced BCI technology.

2. RELATED WORK

There are a large number of localization and object identification systems, using GPS for outdoor applications, or indoor beacon systems such as RFID, Bluetooth, infrared or ultrawideband radio[1]. Most of these wide-area systems can only determine position, but not viewing direction. In contrast, the ID CAM by Matsushita et al. [7] determines

[1]http://www.ubisense.net

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frequency-encoded patterns from blinking beacons in the environment observed by a camera. In this work, we present a related approach using the human visual system. Unlike location systems, the origins of BCI are not in human-computer interaction, but in assistive technology. However, there has been a lot of work in using BCI as assistive technology.

Recently there has been some interest on using variants of BCI technology for non-handicapped people, in order to control aspects of a user interface with little or no attention required from the user. For example, Mann [5] uses biosignal feedback processing for controlling the brightness of a head-mounted display, while Lee and Tan [4] uses EEG for task classification. Chen and Vertegaal [2] use EEG for determining mental load with the aim of managing interruptions .

A similar goal is pursued by Vertegaal et al. [17]. They use a different sensor type, namely eye contact sensors, to control interruptions from cell phones. This work exploits gaze direction to derive information, an aspect that is shared with the work presented in this paper. Velichkovsky and Hansen [16] suggest a combination of eye sensing and BCI control electronic devices . They state their paradigm as "Point with your eye and click with your mind". This suggestion is actually surprisingly close to our intention, and we believe that in this paper we present one of the first practical implementations of such control.

Using the EEG as a biometric is relatively new compared to other methods. Various types of signals can be measured from the EEG, and consequently several aspects have been investigated in terms of user recognition or authentication. Poulus et al. [15] used autoregressive parameters which were estimated from EEG signals containing only the alpha rhythm (eyes closed). Learning Vector Quantization neural networks were used for classification with a 72 - 80% of success. A similar approach was performed by Paranjape et al. [14] which also used autoregressive modeling. They applied discriminant analysis with a classification accuracy of 49% to 85%. Here subjects were tested with both eyes open and closed. Visual evoked potentials (VEP) were used for biometrics by Palaniappan et al. [13] [11] [12]. In these studies, the authors investigated the gamma band range of 30-50 Hz from VEPs after visual stimuli. In the work by Marcel and Millan [6], the power spectral density (PSD) was used from 8-30 Hz for analyzing the repetitive imagination of either left hand movement, right hand movement or the generation of words beginning with the same random letter. A statistical framework based on Gaussian mixture models and maximum a posteriori model adaptation was used in these experiments. In this work the authors conclude that some mental tasks are more appropriate than others, the performance degrades over days, and using training data over two days increases the performance.

3. BCI FOR GAZE DIRECTED OBJECT SELECTION

3.1 Background

Biosignals, such as EEG, can be used to detect human gaze for object selection in the physical environment. This approach is similar to RFID tags or ID CAM, but a mobile scanner is replaced by human perception. Therefore the approach is essentially a form of gaze tracking. Gaze tracking is normally accomplished by observing a user s pupils with a computer-vision system. In our case, a user's gaze is tracked by detecting the activation patterns triggered in the brain when gazing at a specific object. Compared to beacon based location determination, such as RFID, gaze based selection has a wider range of operation and allows to distinguish close objects based on the bearing.

One mental strategy for operating an EEG-based BCI is motor imagery, another is to focus gaze and/or visual attention to a flickering light source. In the latter case, either a late cognitive component with a latency of 300 ms (P300) after rare or significant visual stimulus has to be detected, or the amplitude of the steady state visual evoked potential (SSVEP) has to be measured. The SSVEP is a natural response of the brain evoked by flashing visual stimuli at specific frequencies between 6-30 Hz. SSVEP signals are enhanced when the user's focuses selective attention (focus gaze) on a specific flashing light source [10].

While the P300-based BCI needs complex patterns recognition algorithms to check the absence or presence of the P300 component, the SSVEP-based BCI is simpler and can use a linear threshold algorithm for detection of an amplitude increase of the SSVEP signal. A further advantage of the SSVEP-based BCI is its ease of use and the relatively short training time.

Today, SSVEP-based BCI is used to control a robotic hand [9], secondary cockpit functions [8], the display of geographic maps, or communication (spelling) systems [3]. The highest information transfer rate reported is between 60-70 bits/minute.

3.2 Gaze Tracking Procedure

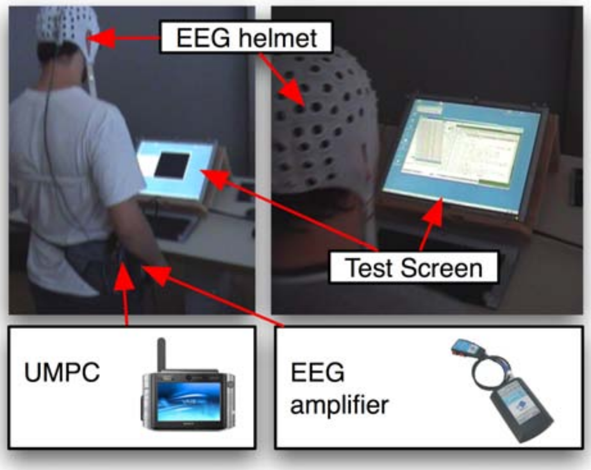

Figure 1: Wearable BCI setup consisting of an EEG helmet and a mobile EEG amplifier both connected to a UMPC. In the experiment test screens show a blinking window as a screensaver and the desktop of the UMPC after a successful BCI triggered login.

In our setup, a mobile user is equipped with a wearable computer (Sony Vaio UX280p) and a portable EEG amplifier (g.tec mobilab[2]) as shown in Figure 1. Wearable com-

[2]http://www.gtec.at

puter and EEG communicate via a Bluetooth personal area network. The user wears a cap fitted with electrodes.

A characteristic blinking frequency of an observed object can be determined with the EEG. This allows multiple frequencies to be distinguished within a few seconds. By setting up physical objects to emit blinking patterns, for example using LEDs or computer screens in the environment, it is possible to identify these objects.

The most obvious way is to directly encode the id of the perceived object using any combination of frequency multiplexing and time multiplexing. For example, an IPv4 address has 32 bits, which once transmitted and decoded could be used to access a web service. However, using current BCI technology, the achievable bit rate is very low, requiring the user to wait too long for the data to be transmitted.

Therefore, the observed characteristic frequency is used as an index into a central directory service accessed wirelessly from the wearable computer. The directory server returns the actual object id or network id (IP address in case of a computer terminal).

To increase the number of addressable objects, the search space is organized hierarchically using a second, complementary sensor system besides EEG. A sensor system (in our case Ubisense) provides coarse wide-area location. The location system is used to limit the search space to one room, and the BCI gaze detection selects one computer terminal within this room.

4. REMOTE, SECURE DESKTOP ACCESS

In [1], a location system based on ultrasonic sensors worn by the users of a large office environment is used to implement various ubiquitous computing services based on the observation of user location.

For example, every computer terminal can be remotely accessed using the Virtual Network Computer (VNC) service. Likewise, incoming calls can be automatically routed by the telecom system to the office phone nearest to a roaming user.

In our setup, the wearable computer can be used to directly connect to a local computer terminal to use the input and output peripherals, while the displayed applications actually run on the wearable computer. In a conference or seminar room, the wearable computer could also be connected to a video projector to give a presentation. The overall procedure is shown on the right in Figure 2. For secure remote desktop access, the user is interested in determining and verifying the identity of the selected object at a particular location, to establish a secure communication channel.

The secure channel is based on CSpace[3], an open source secure communication framework. It uses public key cryptography (PKC) to allow distributed applications to communicate securely without burdening application developers with the details of establishing secure connections. CSpace registers a unique id, public key and current IP address in a global directory.

An application uses a local CSpace proxy object to obtain the user's public key and IP address from the global directory. Then a secure connection tunnel is established to the destination, which looks to the client application like an ordinary TCP connection.

In our implementation, a user can connect the VNC ses-

[3]http://www.cspace.in

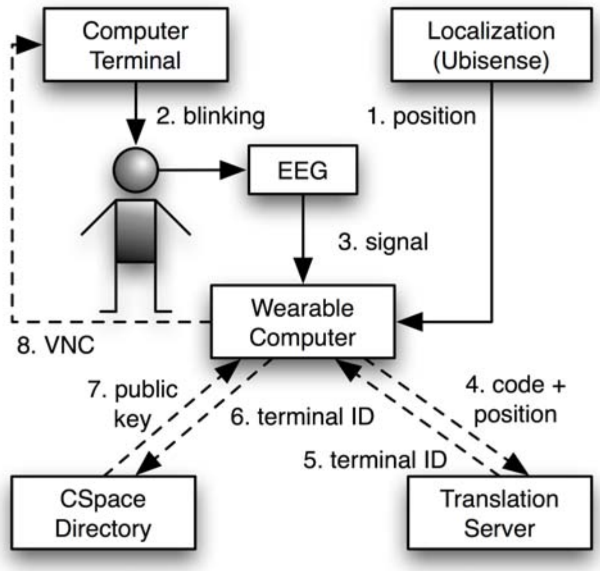

Figure 2: Workflow for establishing a secure VNC connection to a computer terminal after the terminal has been identified using BCI: (1) Localization service determines position, (2) user observes characteristic screen blinking, (3) from EEG signal the code is detected, (4) code and position are transmitted to translation server, (5) translation server returns terminal id, (6) terminal id sent to CSpace directory, (7) CSpace directory returns public key of terminal, (8) secure VNC session established with terminal using public key.

sion originating at the wearable computer to the computer terminal selected by gazing. The current position is determined from a Ubisense indoor location system which covers a large portion of our office space, and the screens of the computer terminals have been set up to run a screen saver emitting characteristic blink patters picked up through the EEG. The combined code position/frequency is transmitted to a global translation service, which translates the code to a CSpace id. This step is necessary because CSpace ids are globally unique and cannot be chosen arbitrarily.

Since the CSpace directory itself is based on an existing peer-to-peer infrastructure (Kademlia), it cannot be extended with the map service directly. Therefore the translation service was implemented as a new service using the CSpace communication infrastructure. Read access works as described above, while write access for updating position or frequency of a particular computer terminal is secured using the private key associated with the terminal's CSpace id. A client tool for the translation service can be used to connect securely to the map service for updating the map, and also launches the appropriate blinking widget used to trigger the EEG.

5. EXPERIMENTS

SSVEP was first tested using a setup consisting of two similar screens placed in front of the subjects, each presenting an individual stimulation pattern (flickering). Screen 1 showed repetitively code 1 *pause (6s) - f1 (4s) – pause (1s) – f2 (4s)*, whereas screen 2 presented code 2 *pause (6s) – f2 (4s) – pause (1s) – f1 (4s)* presented.

EEG was bipolarly recorded from one occipital position (O1 or O2, subject-specific) and digitized with a sampling frequency of 256 Hz. A lock-in amplifier system (LAS) was used to extract the SSVEP amplitudes of 2 specific frequencies (f1=6.25 Hz and f2=8.0 Hz) and their harmonics (up to 3). A simple one versus rest classifier was used to distinguish between those frequencies [7]. A correct login was performed when the pattern of the detected frequencies represented either code 1 or 2 (C1 or C2).

Four different runs (lasting max. 5min, pause was defined with 30s) were performed to validate the functionality of the login classification:

- run1: pause-C1-C2-pause-C2-C1-pause-C2-pause-C1
- run2: pause-C2-C1-pause-C1-C2-pause-C1-pause-C2
- run3: lasted 2min, reading newspaper, no login
- run4: pause-C1-C2-C2-C1-pause-C2-C1-C1-C2-pause

Results of SSVEP-based login shows following results (Table 5): TP (true positives, correctly logged in, max. 20 TPs in whole experiment, FN (false negatives, incorrect logins), FP (false positives, logged in, although no login was required).

A more practical experiment was carried out using the mobile setup from Figure 1. In this setup the UMPC was running a modified version of CSpace to connect to three different PCs. The screens of the test PCs showed a blinking pattern transmitting a 2-bit code registered with a translation service as shown in Figure 2, while the UMPC was running the signal processing routines for frequencies of 6 and 9 Hz. Whenever a valid machine code was detected by the BCI software, a remote login to the corresponding test PC found using the translation service was initiated.

The setup was tested with 2 participants. Participants had to perform the following sequence of remote login tasks: pause (no login, 30s) – login P0 – login P2 – login P1 – pause (30s) - login P2 – login P0 – login P1 – pause (30s). Table 2 shows the results. Both users could successfully complete the tasks. However, we noticed errors. Login times were ranging from 15s up to three minutes with a median of 27.5s and a standard deviation of 51.2s.

6. CONCLUSIONS

We have shown that it is possible in principle to use BCI for biometric communication useful in deploying ubiquitous computing services. However, significant improvements are required to make such services practical in terms of robustness and information transfer rate, which are currently very low. Higher rates can be achieved by more efficient BCI (such as the laser based BCI currently being developed), reducing the intervals of blinking stimuli/pauses, exploiting phase as well as amplitude information and than two blinking frequencies. Even more exciting is the possibility to use subject-specific frequencies and sample positions, which may yield better efficiency but also allow to create unique signatures per human which cannot easily be forged and allow two-way authorization between human and environment.

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Subject	T1	T2	T3	T4	T5	T6	T7	T8	T9
TP	20	9	20	16	19	17	14	20	12
FN	6	11	1	11	11	12	9	1	9
FP	9	5	0	2	6	5	7	0	3

Table 1: Results of SSVEP-based login.

Subject	TP (max. 6)	FN	FP	Total time [m:s]
T1	6	9	1	7:46
T2	6	3	1	5:25

Table 2: True positives (TP), false negatives (FN) and false positives (FP) measured for subjects T1 and T2.

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