Involuntary postural responses of users as input to Attentive Computing Systems: An investigation on head movements

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Involuntary postural responses of users as input to Attentive Computing Systems: An investigation on head movements

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ABSTRACT

Automatic motor or involuntary postural behaviors of users have been receiving an increasing interest in recent years, as unobtrusive measures of cognitive states. In this paper, we investigate the involuntary postural responses of seated users derived from their cognitive changes as input for Attentive Computing Systems. The paper first introduces seated posture, its advantages for cognitive state assessment and connections with cognitive states and, related studies in order to provide a research background for this emerging area of research. We then focus on head posture of seated users and examine the involuntary head movements correlated with task engagement and changing task difficulty through an experiment conducted using a display-oriented cognitive task with changing difficulties. The experiment included 31 participants. Based on different measures, head response and speed, data gathered from user studies were analyzed. Repeated measures Analysis of Variances revealed that head response and speed could serve as cognitive engagement measures. The results indicated that participants get closer to a computer display and became more stationary when they were engaged in a task. The task difficulty analysis results, conversely, partially fulfilled our initial expectations. Head response and speed exhibited limited sensitive behaviors as task difficulties changed.

1. Introduction

As computing technologies evolve and become more prevalent, computing devices with increasing capacities and novel features are added to daily life. These devices, in addition to their appealing services and accompanying opportunities, bring extra burdens to users, including being constantly available for communication, increasing multitasking and adapting to quick changes in the environment. With every device introduced, such burdens become heavier and resulting information overload has gradually become a more serious problem. Users, conversely, cannot avoid the negative consequences of this situation, often because of economical and social reasons, and must cope with associated troubles, including stress and anxiety.

However, according to Roda and Thomas (2006), the real cause of users' troubles is not information overload or the excessive amount of information surrounding users. Instead, the format of this information is too formalized and conventional, lacks context and is cognitively more demanding. Accordingly, information overload is actually a natural part of life. The amount of information directed to humans' sensory organs has always been beyond their processing capabilities. But humans, due to their attentional mechanisms, could manage and live with information overload until the advent of modern technologies.

Attentional mechanisms allow humans to select relevant information for further processing (remembering, inferring, problem solving, etc.) while filtering out irrelevant information (Roda & Thomas, 2006; Wood, Cox, & Cheng, 2006). There is much to say about these complex and crucial mechanisms but we content ourselves with one of their basic characteristics which truly concern us: these mechanisms exhibit limited performance in reality. When interrupted or overloaded, users inevitably receive increasing error rates and task completion times, as well as the accompanying frustration and motivation losses (Bailey & Konstan, 2006; Vertegaal, Shell, Chen, & Mamuji, 2006). As perhaps the most noticeable modern technologies, computing devices are good candidates for the source of such interruptions and overloads due to their inattentive behaviors (Dirican & Göktürk, 2009).

Vertegaal et al. (2006) relate the inattentive behavior of computing devices with their socially inadequate designs such that these devices are not good at determining the volume, timing and channel of their communications. Accordingly, early computing devices were passive tools waiting silently for user's attention. However, today's computing devices and even systems embedded in the environment are "active communicators" that continuously interrupt and overload users with attention requests. Traditional design approaches could thus no longer meet the needs of these information-hungry devices and systems. Newer interaction

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design approaches are needed to provide computing device and systems with the necessary social adequacy, for more natural and unobtrusive communication with users, like Attentive Computing Systems (ACSs) Dirican & Göktürk, 2009.

An ACS basically aims to create efficient interaction methods by regulating communication between users and computers in a social manner (Vertegaal et al., 2006), to augment users' attention for better task and system performances (Vertegaal, 2003; Zhai, 2003) and to support users' information needs relevant to their interests (McCrickard & Chewar, 2003). To reach these aims, ACSs need a deep and multidimensional user understanding based on information about users' attention (past, present and future), cognitive states (cognitive workload and engagement), intentions and priorities (Dirican & Göktürk, 2009; Roda & Thomas, 2006; Vertegaal et al., 2006). The literature offers different approaches to provide such understandings that exploit different explicit or implicit information channels, ranging from application use and web browsing to psychophysiological measures such as eye-gaze, pupil dilation, EEG and HRV.

Each approach has its own disadvantages. While explicit approaches have trouble providing the necessary multidimensionality (Zhai, 2003), psychophysiological measures may suffer from various weaknesses that prevent them from serving in real environments, including vulnerabilities to confounding factors such as lightning conditions (eye gaze and pupil dilation), muscle activity or sensor movements (EEG) Dirican & Göktürk, 2011; Fairclough, Ewing, & Roberts, 2009; Frank, 2006. Alternatively, users' automatic motor behaviors or involuntary postural responses have recently received increasing interest, as inherent and unobtrusive measures of attention and cognitive states, and more suitable to serve in real environments (Bahr, Balaban, Milanova, & Choe, 2007; Balaban, Prinkey, Frank, & Redfern, 2005; Balaban et al., 2004; Mota & Picard, 2003; Schrammel, Paletta, & Tscheligi, 2010).

Particularly, seated postural responses attract researchers and related studies show that these have the potential to meet the aforementioned user understanding for ACSs. To further reveal this potential, this paper investigates the involuntary postural responses of seated users from a cognitive state assessment perspective. The paper first provide a detailed introduction about seated posture and various related topics, in order to provide a research background for the current and future studies. We then focus on changes in head posture and empirically examine seated users' involuntary head movements correlated with cognitive changes.

We believe that the human head deserve much more attention, as an interesting body part that holds eyes, ears and other organs that shape the face. Head movement and gestures, naturally, convey a rich body of explicit or implicit information about users, needed by modern HCI studies like ACSs. Humans, for instance, have a better motor control of head than eyes to make fine pointing gestures (Morency, Sidner, Lee, & Darrell, 2007). This makes the use of voluntary head movements and gestures possible in areas such as development of natural interaction styles for graphical user interfaces (Morency et al., 2007) and user-sensitive wheelchairs (Lee, Loo, & Chockalingam, 2012).

Freedman (2008) states that since eye movements are neuromechanically restricted (the largest movement does not typically exceed ±40 – 45), humans have to redirect the line of sight by simultaneously moving the head and eyes, to extend these limitations. Besides, when humans shift attention, they first move their gaze and then reorient their head and body orientation as a result of continuing interest to their new focus of attention (Abe & Makikawa, 2009; Yamaoka, Kanda, Ishiguro, & Hagita, 2009). Head orientation is therefore suggested as a measure of users' visual attention to objects or people, alternative to eyes movements (Vertegaal et al., 2006). As an ACS can exploit it to determine users' focus of attention, head orientation also lead several interesting studies, such as measuring drivers' visual distraction (Schrammel et al., 2010) or determining the interests of pedestrians in a shopping street (Metz & Krueger, 2010).

Moreover, voluntary or involuntary head movements and gestures consist of an important part of nonverbal communication among people. Humans are able use these to nonverbally express their own and unobtrusively determine each other's intentions and mental states. In other words, head movements and gestures covey information and therefore provide various means to infer users' affective (Lance & Marsella, 2007; Paterson, Pollick, & Sanford, 2001), cognitive (Bahr et al., 2007) or more complex mental states, including agreement, disagreement, thinking, interest and disinterest (El Kaliouby & Robinson, 2004; Morency et al., 2007). This property of head movements and gesture is quite important for ACSs and can be better explained by how humans perceive activities.

Zacks, Kumar, Abrams, and Mehta (2009) state that during perception, humans segment continuous activity into discrete events and movement variables play an important role within this process called event perception. Accordingly, humans perceive an ongoing activity by segmenting it into meaningful units using in part changes in body configuration and movement, including its direction, speed and acceleration. These findings suggest that changes in users' movements or posture (as a whole or by its parts like head) convey information about their activities and indirectly their intentions and mental states. Thus, we have formulated a number of research questions:

- "How do cognitive changes affect users' involuntary head movements?"
- "How does cognitive engagement affect users' involuntary head movements?"
- "How does changing cognitive workload affect users' involuntary head movements?"

In order to look for the answers to these specific questions, we have designed an experiment to examine the effect of task engagement and changing task difficulty on the involuntary head movements, using two movement variables: head response and speed, with the below expectations.

Since humans exhibit cognitive engagement in shape of orienting movements (Balaban et al., 2004) and intuitively become more stationary to better attend to a complex task, we expect users to exhibit orienting head movements toward monitor and become more stationary, when engaged with a task. Orienting movements are also considered as indicators of cognitive resource allocation to events (Balaban et al., 2004); therefore we can expect changes in head movements toward monitor as a result of changing task difficulty or cognitive workload.

Besides, Frank (2006) suggest that users become more stationary (increasing postural stability) or exhibit less postural changes (torso) as a result of increasing task difficulty. Since head movements are not free from the movements of torso, we hypothesize that increasing stability of human body can be observed in head movements and it can be used a supplementary measure of cognitive state of users. Therefore, we expect users become more stationary as the task difficulty increases or vice versa.

The subsequent sections of this paper are organized as follows. Section 2 provides a detailed introduction about seated posture and related topics from a cognitive state assessment perspective. Section 3 describe the method used in the experiment; presents techniques developed for head tracking and cognitive manipulation, independent and dependent measures used, experimental design and statistical analysis techniques. Then, Section 4 presents the statistical analysis results, run for both the performance and head movement measures of the experiment. While Section 5

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discusses the results presented in previous section, Section 6, finally, provides conclusions and possible future directions.

2. Involuntary postural responses of the cognitive state

2.1. Posture, seated posture and human computer interaction

Posture is a multidimensional construct that can be considered in various ways, including the biomechanical alignment and spatial arrangement of body parts, relative position between segments and body attitude assumed to perform a task (Vieira & Kumar, 2004). It can express humans' voluntary and involuntary or conscious and unconscious motivations and purposes and, can be defined as the positions assumed by the body, as a whole or by its parts, to execute a movement or maintain an attitude (Deutch, 1947). This multidimensional nature of posture encourages various studies in Human Computer Interaction (HCI). As an implicit and unobtrusive information channel, these studies take advantage of posture, statically or dynamically:

1. As a direct input mechanism, it is an alternative to keyboard, mouse and joysticks (Loke, Larssen, Robertson, & Edwards, 2007).
2. As a cue of physical state and user activities, it creates input for ambient intelligence systems (Cucchiara, Grana, Prati, & Vezzani, 2005).
3. As a cue of a user's mental state and intentions for Attentive Computing and similar systems, including context-aware, perceptual and affective (Abe & Makikawa, 2009; Bahr et al., 2007; Balaban et al., 2004; El Kaliouby & Robinson, 2004; Frank, 2006).

The actual number of postures that a body can assume depends on its degrees of freedom (Boulay, 2007). Though numerous postures can therefore be considered, humans are usually in a common posture, such as lying, kneeling, crouching, standing or sitting. Among these, standing and sitting have always had an exclusive place, as these postures are the most common in the workplace (Li & Haslegrave, 1999). However, the seated posture has recently received more attention due to the increased occurrences of sedentary tasks and changing lifestyles. As a result of technological advancements, not only in offices but also in homes and schools, people have increasingly been staying seated throughout the day. This situation has made the seated posture an interesting research area in HCI and is already studied in different domains, including home, office, education, automotive and assistive technologies (Mutlu, Krause, Forlizzi, Guestrin, & Hodgins, 2007).

When performing posture-related research, factors affecting one's posture must be seriously considered to set up better experiments and obtain more accurate results. Fortunately, the ergonomics literature provides important and ready-to-use knowledge about these factors. Accordingly, posture is principally influenced by task factors, workstation design, tools used (equipments and materials), physical workplace arrangement and an individual's anthropometric characteristics (Vieira & Kumar, 2004). Specifically, seat design affects the seated posture, especially in its inclination, backrest position and the shape and presence of an armrest (Magnusson & Pope, 1998).

Task factors have special effects on posture. Li & Haslegrave (1999) state that the adoption of a work posture is almost always purpose oriented or task based and is likely influenced by these factors. In their study (Li & Haslegrave, 1999), they investigate the effects of the manual and visual demands of a task on seated posture, showing that both the visual and manual difficulties of a task affect posture, even more so if they are presented together. Moreover, coordinating the head and torso can adjust one's posture to better meet the visual demands of the task. In a similar study conducted by Hsiao & Keyserling (1991) conversely, posture was found as correlated with body size, target location and target size. The authors concluded that both the visual activity and manual manipulation needs of a task may determine the posture.

2.2. Seated posture as a cognitive state cue

Though it may cause different musculoskeletal health problems, like lower back pain, the seated posture provides many advantages over standing, including (1) fewer loads on lower extremities, (2) lower energy consumption and (3) stability needed for tasks with high visual demands and motor control (Hsiao & Keyserling, 1991). These advantages, especially the last, explain why humans sit during tasks that require a specified amount of visual, cognitive and motor capacities and concentrations, ranging from reading to automobile driving. The seated posture can therefore be considered as an important cue for the visual, motor and cognitive demands of users' ongoing activities.

However, binary information indicating whether a user sit or not is simply not enough to make accurate predictions about these activities. Additional information or measures are required about how users' seated-postural behavior exhibits changes in relation to their cognitive states and changing task conditions or task demands. To acquire such measures, users' seated postural changes must be recorded in real time and investigated under different tasks, under changing task demands and indirectly under different cognitive states.

Fortunately, users are relatively stationary as they sit because the seat reduces the degrees of freedom of body movements (Balaban et al., 2005). This advantage of the seated posture facilitates real-time recording of postural changes using motion trackers (for head, shoulders and upper limbs) and pressure sensors (for buttocks and back). Investigating seated postural changes and relating these changes to relevant cognitive states, however, depend on understanding the nature of postural changes caused by cognitive alternations, as discussed in the following section.

2.3. Origins of cognitively meaningful postural changes

Existing research indicates that postural changes reflecting cognitive states or users' postural responses to cognitive changes are principally derived from degradations in users' postural control or nonverbal communicative expressions.

Postural control is the control of the body's position in space for balance and orientation (Woollacott & Shumway-Cook, 2002). As the human body is bipedal and has an articulated structure, it is inherently unstable and therefore needs to be stabilized, especially for a proper upright stance (Peterka, 2002). However, stabilizing this inherently unstable system and controlling its position in space are significantly complex operations, performed through multimodal sensory information from different body subsystems, including the visual, proprioceptive and vestibular systems (Peterka, 2002).

Moreover, recent studies have demonstrated that postural control is not independent of humans' cognitive mechanisms. Although postural control has been considered a fully automated and reflex-controlled task until recently, dual-task studies have indicated that it also requires a certain amount of cognitive resources that depend on the postural task, individuals' ages and their balance abilities (Woollacott & Shumway-Cook, 2002). As a result, degradations in either the sensory or cognitive sides of postural control may reduce body stability and thus cause instability. When this instability is detected as originating from a dual-task situation with accompanying decreases in task performance, it can be an important cue for task demands and the user's cognitive state.

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This premise is well documented in the literature, especially for the standing posture (Alghanim, 2009). Many studies have investigated the influence of concurrent motor and cognitive tasks on postural stability through dual-task performances (Alghanim, 2009; Frank, 2006; Schmid, Conforto, Lopez, & D'Alessio, 2007; Woollacott & Shumway-Cook, 2002). The results suggest that standing posture control requires a certain amount of cognitive capacity such that increasing the cognitive load (the difficulty of a cognitive task) causes degradations in postural control/stability and users to sway more. Due to the advantages of seated postures over standing (Section 2.2), however, asserting a similar relation between seated posture control and postural stability is not easy. Moreover, the study of Vette, Masani, Sin, and Popovic (2010) strengthens this idea and the results presented indicate that humans are more stable during quiet sitting than quiet standing (for quite sitting, subject's' body sway size and velocity are smaller than for quiet standing).

Though some studies, discussed in Section 2.4, indicate that users exhibit meaningful postural responses when sitting as a result of cognitive changes, including attending, focusing and engaging, we think that the seated postural responses reported in these studies mostly originate from nonverbal communicative expressions exhibited by users. These expressions thus deserve an exclusive interest in cognitive state assessment, especially for seated users.

Nonverbal communicative expressions, or simply nonverbal communication, are significantly important in human–human communication, allowing users to communicate efficiently, cooperate and share the same environment in harmony (Akakın & Sankur, 2011; Alghanim, 2009; Morency et al., 2007). Humans can unobtrusively make accurate predictions about each other's mental states and feelings by observing each other's nonverbal actions, including facial expressions, gestures and postural behaviors (Akakın & Sankur, 2011; El Kaliouby & Robinson, 2004; Lance & Marsella, 2007; Vertegaal et al., 2006). These can convey the degree of engagement, concentration and desire for interaction or isolation (Bahr et al., 2007).

For instance, consider an individual sitting in front of his or her computer in a position leaning toward the monitor with both the torso and head, with a serious facial expression and remaining almost stationary. One can inherently evaluate this as individual in question is working with high concentration and possibly focusing on an important task. An Attentive Computing System, conversely, can make a similar evaluation based on the following nonverbal communication principles.

Orienting movements, like leaning forward toward the monitor, are indicators of cognitive engagement and the level of a human's cognitive resource allocation to events, people or objects (Balaban et al., 2005). Head and eye fixations are good indicators of human attention to things or people (Abe & Makikawa, 2009; Lance & Marsella, 2007; Vertegaal et al., 2006). Facial expressions, however, convey a great deal of information about users' affective (i.e., happiness, sadness or anger) and cognitive states (i.e., thinking, deciding or confused) (Bahr et al., 2007; El Kaliouby & Robinson, 2004). If computing systems can interpret these nonverbal communication principles, they can also have the same knowledge about their users' mental state and act accordingly. Thus, human–computer interaction may be designed and conducted as similar (unobtrusively, non-invasively and attentively (Dirican & Göktürk, 2009) to human–human interaction.

2.4. Related studies

Few studies have examined human cognitive state assessment through the involuntary postural responses of seated users. Among them, a series of studies conducted within the USA Defense Advanced Research Projects Agency's (DARPA) Augmented Cognition program (AugCog) provide valuable results for this and future research. These studies show that dynamic seated postures exhibit meaningful patterns under changing task conditions and cognitive changes, using a Visual Display Terminal (VDT)-oriented military task, the Warship Commander Task (WCT) (Balaban et al., 2004).

The WCT is a simulated air-space defense task with changing difficulties. The aim is to monitor incoming waves of aircraft (friendly, hostile or unidentified) that enter the defense perimeter of a warship and take necessary actions (do-nothing, neutralize, IFF or warn), in a series of 75-s trials. The task difficulty is specified by total number of aircraft on screen (6, 12, 18, 24), ratio of unidentified aircraft to the total number of aircraft at any given time and an auditory/verbal memory recall task.

Seated posture is modeled on three dependent variables in these studies: the head (monitor engagement), seat-back or back-bracing and seat-bottom responses. Head response is defined as the movement of the head relative to the monitor in the anterior/posterior direction, measured by a magnetic head tracker and markers attached to a subject's head and seat (as a reference to movement). Back-bracing and seat-bottom responses, conversely, are pressure changes measured by sensor arrays embedded in the upholstery of the seat back and bottom.

The results of these studies indicate that subjects exhibit postural changes in the shape of orienting movements towards the display monitor as an important cognitive engagement cue. Head response, for example, is correlated by the number of aircraft on the screen (Balaban et al., 2004). Subjects get close to screen at a small magnitude (1–10 mm) during the first half of a wave. They remain fixed at a plateau until the end of the wave. Therefore, display engagement head response is reported as a global (tonic) indicator of cognitive engagement.

Similar to head response, the seat-bottom response also correlates with number of tracks on the screen, reflecting postural shifts relative to the display monitor at the onset of waves (Balaban et al., 2005). Based on the center of pressure values separately calculated for the left and right buttocks, it is also suggested as a global measure of cognitive engagement. Similar findings are reported for an in-vehicle experiment in this study (Balaban et al., 2005).

The back-bracing response, conversely, is suggested as an instantaneous (phasic) measure of task demands or cognitive loads, similar to when humans brace themselves in heavy traffic against the seat and steering wheel (Balaban et al., 2004). Accordingly, humans brace themselves until they perceive an easing in the task workload. Additionally, according to the results of the study conducted by Frank (2006), the seat-bottom response is also suggested as a global measure of task difficulty or cognitive load. The results indicate that decreases in postural changes are observed parallel to increasing task difficulty. This decrease is observed and calculated in different dimensions of seat-bottom response. During the hardest level of the task (24 tracks on screen), for instance, the distance travelled by the seat's center of pressure and the transverse-plane seat torsion decrease by 40.3% and 32.2% respectively, compared to the simplest level (6 tracks).

In a separate study Mota and Picard (2003) uses the seat-bottom and back pressure measures for affective state assessment or, more specifically, inferring the interest level of children playing a video game using different classification techniques. They first classify 9 specific postures with 82.3% success, including leaning forward, leaning backward or sitting on the edge of a seat. Using these specific postures, their system predicts interest levels of children with 76.5% accuracy, based on three interest levels.

3. Method

In this study, we hypothesized that users' involuntary head movement responses correlate with task engagement and changing task difficulty. To test this, we developed a test bed with a height-adjustable camera mounted on the ceiling, shown in Fig. 1, a vision-based head tracking method and a cognitive manipulation task. Using the experimental setup, we conducted laboratory experiments described below.

3.1. Participants

We recruited 31 participants from departmental undergraduate students and staff for the experiment. Their ages ranged from 20 to 32 years ($M = 23.48$, $SD = 2.90$). Of the participants, 20 were males and 11 were females. No participants had any specified physiological or musculoskeletal disorders. During the experiments, 8 wore eye glasses or contact lenses. Participants had an average of 8 years (*SD*: 4.07) of computer usage experience and spent approximately 7.32 h (*SD*: 3.74) of a day in front of a computer. They rated their game playing frequency as 2.03 (*SD*: 1.16), from 0 (not interested) to 4 (playing frequently), game playing expertise as 2.03 (*SD*: 1.07), from 0 (not interested) to 4 (expert gamer) and average weekly game playing time as 3.85 h (*SD*: 5.14). These statistics indicated that participants in this experiment were young adults with certain levels of computer usage and game playing experience.

3.2. Equipment

The experiments were conducted using a moderately configured high-end personal computer with a 19″ Flat LCD monitor display, a standard keyboard and a standard mouse. Participants sat in an office-type chair in front of a standard office desk and monitored by a Logitech™ 905 HD camera from the ceiling. The camera was mounted to the ceiling with a specially designed adjustable camera clip. The connection between the camera and PC was realized using a 5 m Digitus USB extension cable.

The same PC was used for both the experiments and data acquisition. A color marker-based tracking application and cognitive task were developed using OpenCV and OpenGL libraries. The monitor location and head movements were tracked by a tracking application, with a red rectangular marker attached to the monitor and a specially designed tracking cap, both shown in Fig. 1. An additional application was developed for data synchronization, using data gathered from the tracking application and cognitive task. All applications were implemented in Microsoft Visual Studio using C++. Data were prepared for statistical analysis using Matlab routines, and SPSS was used for statistical analysis.

3.3. Head tracking

A vision-based head tracking system was developed and used in this study. The system was designed to continuously track head movements in space and record the corresponding spatial and temporal information. Head movement changes in the transverse plane and head orientation were calculated with a specified precision and speed in relation to a given video frame resolution. For example, participants' head movements were monitored at 4.97 Hz frequency for a 1280×1024 resolution in this study. We used such a large resolution to obtain more precise tracking results because they are important in posture analysis applications.

The system used a color marker-based tracking method and was tracking head movements using red spherical markers, namely head markers, placed on participants' heads (Fig. 2). It was also tracking the display location with a red rectangular marker placed on its upper edge. Head markers were purposely selected from rigid spherical objects because their appearances remain the same as they rotate, and their centers do not change when they move in any direction. As a participant moved his or her head, the marker shape became invariant (it appeared like a disk). The marker center thus provided a reliable base point for tracking. Size changes could also provide a depth approximation (distance from the camera).

As reference points that were tracked instead of real objects of interest, markers must have stayed fixed and appropriately segmented. Therefore, they had to be carefully and firmly placed on objects. In our system, head markers were attached to a black plane, called the marker plane, affixed on a black hat worn by participants during experiments, called the tracking hat. The marker plane was covered by a black fabric to attenuate undesired reflectance effects and acquire better detection results by isolating them from the rest of the scene.

Markers were detected by a complete segmentation algorithm based on hysteresis thresholding (Fig. 2a) and color information in RGB space (Petrou & Bosdogianni, 1999). The result of hysteresis thresholding was then analyzed using a connected component analysis. After labeling separate regions with different numbers, the detection was finished (Fig. 2b). Finally, feature descriptors of these regions were computed, including width, height and central coordinates. These features then could be used for tracking. In this study, once the detection algorithm provided the descriptors of possible markers, the display marker (only once) and spherical objects (continuously) in the scene were located by their relative geometric positions and sizes. Later, all values in a pixel were transformed into centimeters based on the camera's field of view.

3.4. Task

A display-driven cognitive task, shown in Fig. 3, to impose different cognitive loads on participants, was designed and used. The task was a computer game with varying difficulties played with a mouse. There were circular objects moving across the screen. An object was entering the screen from the left or right

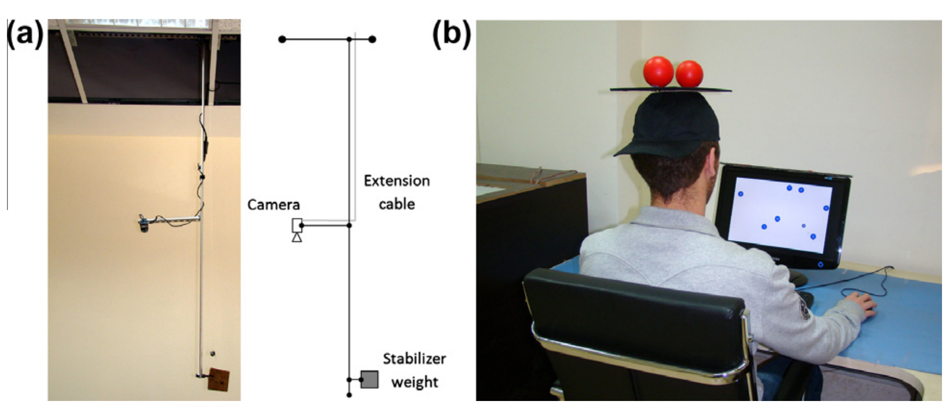

Fig. 1. Equipments and test bed: (a) Custom-fit ceiling mounted adjustable camera clip. (b) Picture of a participant wearing tracking hat.

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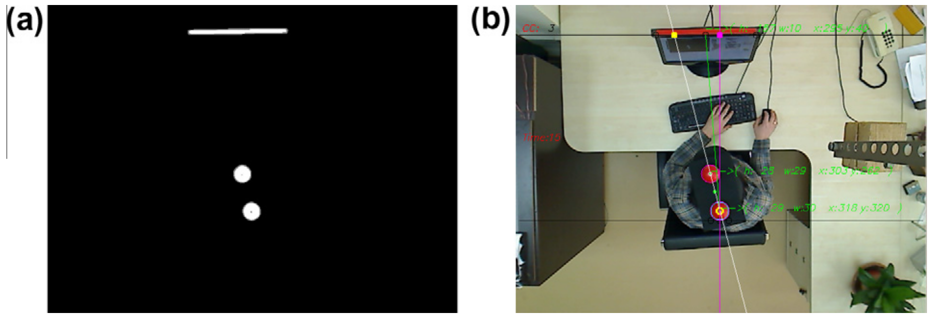

Fig. 2. Screens from tracking method: (a) Segmentation result. (b) Located markers and their demonstration on real scene.

edges, randomly selected in each turn. The object was then moving toward the opposite side with a fixed speed and random angle, between −15° and 15°.

Each object carried either an even or odd number. Objects that carried even numbers were treated as targets and objects with odd numbers as friends. The ultimate goal was to eliminate all targets that cross the screen by clicking (single left click) on them (target-hit). The following actions were forbidden: (1) killing friends (friendly hit), (2) unnecessary clicks on the screen or multiple clicking on targets (surface-hit) and (3) missing or overlooking targets (miss). While target hits resulted in positive points, all forbidden actions resulted in negative points.

The difficulty of the task could be adjusted by changing the target-friend ratio on screen and the objects' moving speed. In this study, the only manipulated variable was the target-friend ratio. The target number was fixed to 4. By increasing or decreasing the number of friends on the screen, the task difficulty was specified in the order of 4, 12, 0, 16 and 8. Consequently, the number of maximum circular objects on screen was 8, 16, 4, 20, and 12 at 5 consecutive levels.

This task required (1) focusing on a continuously changing surface (global awareness Balaban et al., 2005), (2) searching with the eyes and head (local awareness Balaban et al., 2005), (3) locating and tracking targets by discriminating even and odd numbers (cognitive processing) and (4) clicking on selected objects without making errors (hand-eye coordination problem). As a result, by increasing the number of friends on the screen, we intended to ensure that participants made more searches and consequently committed fewer target-hits, had trouble discriminating the circular objects (miss and friendly hit) and faced performance problems while clicking without making errors.

3.5. Procedure

Controlled experiments were conducted in the Human Computer Interaction Laboratory of the Gebze Institute of Technology. Participants were tested individually and were not told the real purpose of the experiment until the completion of all procedures. Although they volunteered for the experiment, participants were offered small gifts, such as chocolates and candies, after being welcomed to the lab. Before the experimental stage, every participant signed a consent form.

Participants first wore the tracking hat. After ensuring that the hat was correctly placed on the participant's head, the tracking system and task software were run. When the participant was ready, the training session started. In this session, the task was first explained in detail. After providing the required explanation, participants performed a 1-min training task before progressing to the test session. Before this session, participants were motivated to be successful by hitting as many hostile objects as possible in this

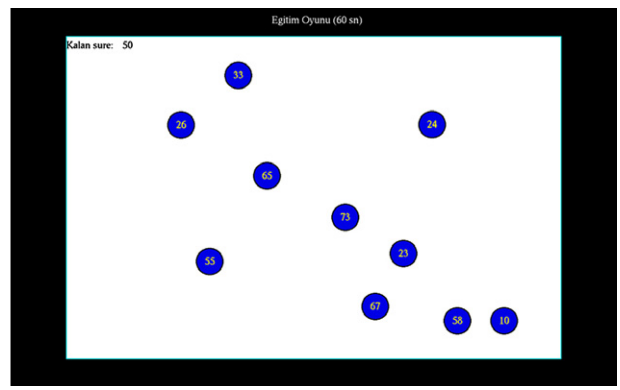

Fig. 3. Screen from the training stage of the task used in the experiment.

stage and avoiding making friendly hit, surface-hit and miss errors. They were also asked to focus on the task and behave as naturally as possible.

Before starting the first task session, as a control situation, a 10-s countdown was visually represented on the screen, and participants were asked to watch the decreasing numbers from ten to zero and do nothing. They then completed 5 consecutive 90-s stages with varying difficulty levels. After the experiment, every participant filled out a questionnaire, including information about him- or her-self and the experiment.

3.6. Measures

There were one independent variable and two groups of dependent variables in the experiment. The independent variable was the level of task difficulty or the number of friendly objects on the screen that change in the order of easy-difficulty strategy (Rowe, Sibert, & Irwin, 1998). Dependent variables, conversely, were performance and postural measures.

Performance measures were the success (target-hit) and error measures (miss, friendly hit and surface-hit) selected for this task. Postural measures were measures that define different aspects of head movements in the transverse plane (TP) and the anterior/posterior (AP) and medial/lateral (ML) axes. The tracking system basically gave two pairs of dependent variables that model the head movements: coordinates of the spherical object centers and their sizes. These variables could be directly used for analysis. Furthermore, different measures that summarize movement, called summary measures, were computed and used (Schmid, Conforto, Lopez, & D'Alessio, 2007). All postural measures used in this study were computed using the head movement data gathered from the spherical object located near the medial line of the body, shown in Fig. 4. These measures were as follows.

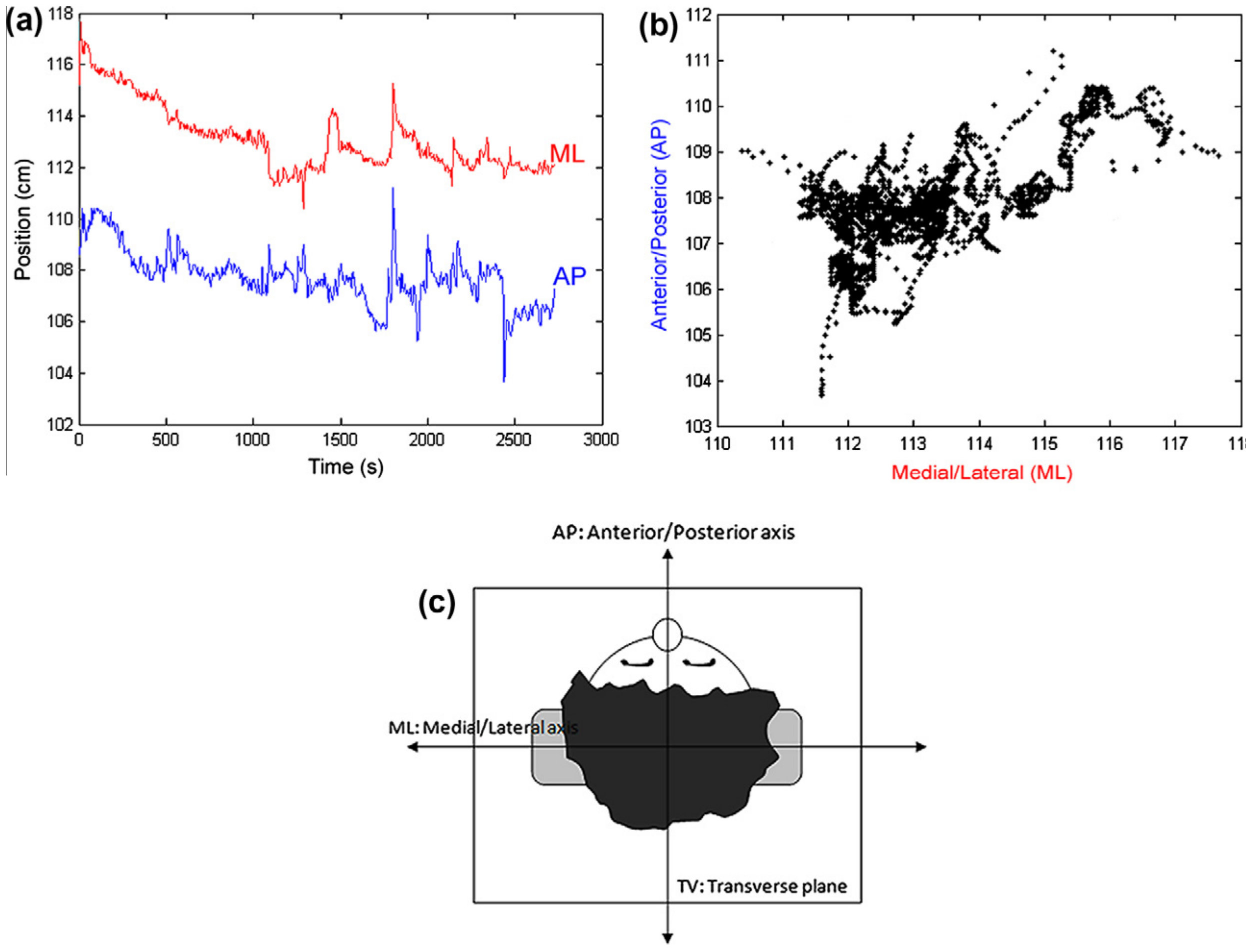

Fig. 4. Head movement data of a participant during the test: (a) In the medial/lateral (ML) and anterior/posterior (AP) axes. (b) Its 2D representation in transverse plane. (c) A representation of the anatomical coordinate plane.

- **Head response**: We defined head response as the change in head movements with respect to a selected base point in the ML and AP axes and conceptually as the response of a user's head to external stimuli. Therefore, when the point at which the external stimuli exposed to a user was selected as the base point, head response could be considered a cue of a user's reaction to stimuli.
- **Head speed**: From a bear physics perspective, head movements could be described as different features of displacement, including traversed path length, speed and velocity in a period of time. The average magnitudes of these values could also be used; their range and standard deviations (variability) could summarize head movements. This study investigated head speed.

3.7. Design and analysis

The experiment was designed and applied as a (1 Trial × 5 Levels) within-subject design. Repeated measures analysis of variance (ANOVA) was therefore used to analyze the effect of changing task difficulty on head response and speed. To analyze the effect of task engagement, participants' average head responses and speeds were analyzed over time during the control condition (10 s) and the first stage of the task (90 s) for 5-s periods over 100 total seconds. To perform this analysis, (1 Trial × 20 Periods) repeated measures ANOVAs were therefore used. Figs. 6 and 7 show that, while the first two periods (5 and 10) belong to the control condition, the remaining ones belong to the first stage of the task.

If analyzed data did not accommodate Sphericity (controlled by the Mauchy test), the Greenhouse E-Geisser Correction was used. For all significant results given by repeated measures ANOVA, Bonferroni corrections were applied, as post hoc tests, to examine statistically significant differences. The ANOVA normality assumption was controlled using Shapiro–Wilky normality tests. If the data violated the normality assumption and ANOVA could not handle it, natural log transformations were applied to the data.

4. Results

4.1. Performance measures: cognitive task

Pearson product-moment correlations were run to determine the effect of changing task difficulty on average user performance or the averages of the success and error measures of this study. Strong and significant as well as negative and positive correlations given in Table 1 were detected, consequently. While a significant negative correlation was detected between task difficulty and success measure Target-hit, significant positive correlations were detected with task difficulty for error measures Miss and Friendly hit. Surface-hit, on the other hand, did not yield a significant correlation with task difficulty.

(1 Measure × 5 Levels) Repeated measure ANOVAs with Bonferroni post hoc tests were then applied to further analyze the discriminatory effect of performance measures on task levels (Fig. 6). Target-hit scores exhibited a statistically significant overall

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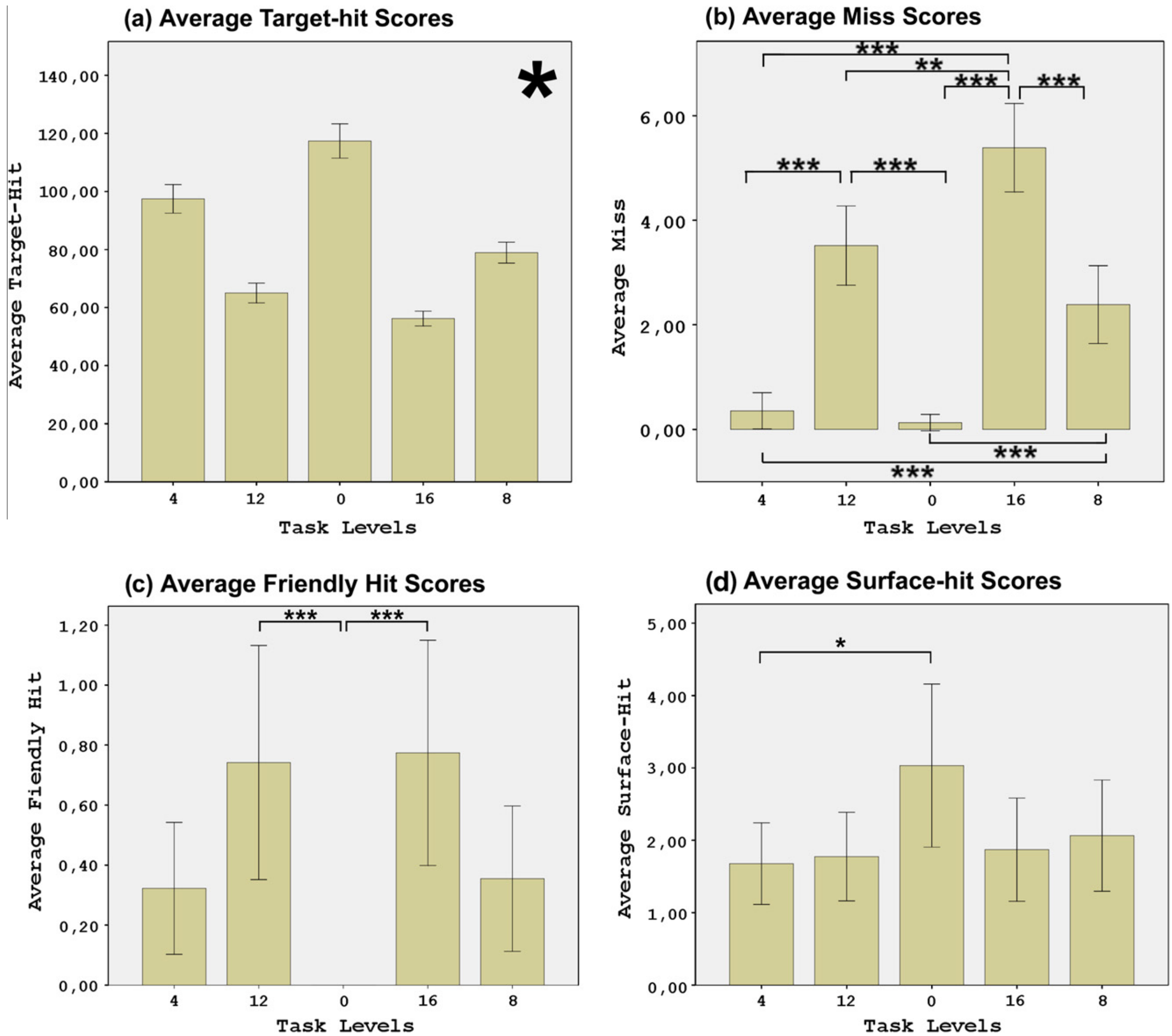

Fig. 5. Performance measure averages. Error bars indicate 95% confidence intervals; *, **, *** indicate significance levels $p < 0.05$, $p < 0.005$ and $p < 0.0005$, respectively, and "*" indicates that there are statistically significant differences between all levels with $p < 0.0005$.

effect on task levels (*F(2.412,* 725.35) = 291.991, $p < 0.0005$) and post hoc test revealed that there was a significant inversely proportional relation between task difficulty and Target-hit (Fig. 5a). Miss scores also exhibited a significant overall effect (*F(3.043, 88.261)* = 59.699, $p < 0.0005$) on task levels and significant differences between almost all levels except levels 4–12 and levels 12–8 (Fig. 5b). These results indicated that there was a linearly proportional relation between task difficulty and Miss.

Moreover, Surface-hit scores had an overall effect on task levels: *F(4.120)* = 3.357, $p < 0.05$) and post hoc tests only revealed that surface hit score at level 0 was significantly greater than level 4. Similarly, friendly hit exhibited a significant overall effect on task levels (*F(2.694,* 80.815) = 5.495, $p < 0.005$) and post hoc test (Fig. 5d) revealed that friendly hit scores at levels 12 and 16 were significantly greater than level 0.

4.2. Postural measures: head response and speed

4.2.1. Task engagement analysis

(1 Trials × 20 Periods) Repeated measure ANOVA and Bonferroni post hoc tests were applied to analyze the effect of task engagement on head response and speed. The data obtained from the experiments were analyzed in anterior/posterior (AP) and medial/lateral (ML) axes and the results depicted in Fig. 6 (head response) and Fig. 7 (head speed) were as follows.

In the ML axis, head response gave an overall significant effect on time periods (F(2.41, 72.240) = 8.959, $p < 0.0005$). Post hoc test (Fig. 6a) revealed that the head response in ML axis was significantly greater at the control condition than the first stage of the task. In the AP axis, head response had an overall significant effect on time periods (F(1.684, 80.605) = 17.110, $p < 0.0005$), as well. Post hoc tests (Fig. 6b) revealed that the head response in the AP axis was greater at control condition than the first stage of the task.

Head speed had significant overall effects on time periods in both the ML (F(9.517, 247.453) = 9.016, $p < 0.0005$) and AP (F(19, 494) = 19.805, $p < 0.0005$) axes. Post hoc tests (Fig. 7) revealed that head speed in both axes was greater at the control condition than the first stage of the task. When it was analyzed in the transverse plane (TV) plane, this effect is commonly observed (F(9.793, 293.79) = 21.515, $p < 0.0005$). The significant differences shown in Fig. 7c indicated that even after the first 5 s of first stage (level 4), the speed continued to decrease.

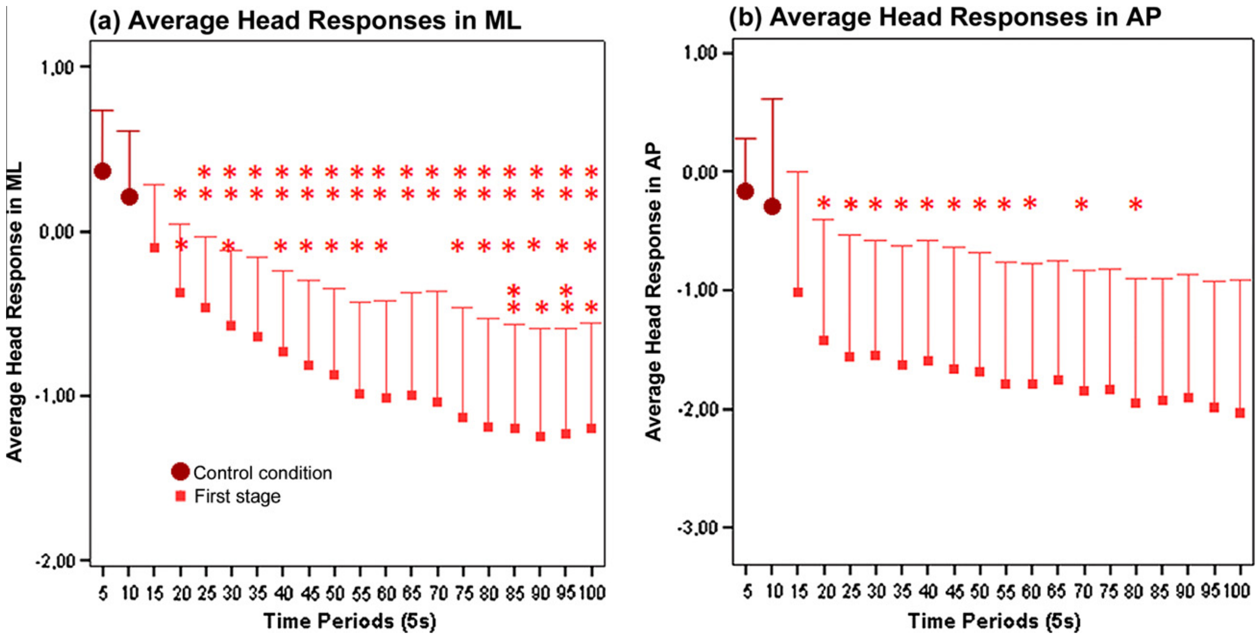

Fig. 6. Averages of head responses for 5-s time periods. Error bars indicate 95% confidence intervals. * indicates significance levels $p < 0.05$ or $p < 0.005$.

4.2.2. Task difficulty analysis

(1 Trials × 5 Levels) Repeated measure ANOVA and Bonferroni post hoc tests were applied to analyze the effect of changing task difficulty on head response and speed. The data obtained from the experiments were analyzed in the anterior/posterior (AP) and medial/lateral (ML) axes and the results depicted in Fig. 8 (head response) and Fig. 9 (head speed) were as follows.

In the ML axis, head response gave an overall significant effect on task levels ($F(2.694, 80.823) = 4.825$, $p < 0.05$). Post hoc tests (Fig. 8a) revealed that the head response in the ML axis was significantly greater at level 4 compared to levels 12, 0 and 16. Head response had an overall significant effect on task levels in the AP axis ($F(1.677, 50.299) = 3.405$, $p < 0.05$), as well. Post hoc tests (Fig. 8b) revealed that the head speed in the AP axis was significantly greater at level 0 than level 16.

In ML axis, head speed exhibited an overall significant effect on task levels ($F(4120) = 6.742$, $p < 0.0005$). Post hoc test revealed that the head speed in the ML axis was significantly greater at level 0 than level 4 and 12, and at level 8 than level 4 and 12. Head speed had an overall significant effect on task levels in AP axis ($F(4, 120) = 4.614$, $p < 0.005$), as well. Post hoc tests revealed that the head speed in the AP axis was greater at level 0 and 8 than level 4.

5. Discussion

5.1. Cognitive task

Before discussing the head movements in response to task engagement and the chancing task difficulty, we believe it is necessary to consider the validity of the cognitive task used in the experiment. Results given Section 4.1 suggested that the task used for cognitive manipulation induced the intended workloads on participants almost as expected, from a ''primary-task'' mental workload measurement perspective,

The basic premise behind primary-task measurement is that a task with a higher workload is more difficult, resulting in degraded performance compared to a low-workload task (Young & Stanton, 2004). Accordingly, as the difficulty of a task (task demand) changes, while declining success with increasing error rates indicates an increase in difficulty, improvements in success with decreasing error rates indicate a decreasing difficulty. While success and task difficulty are inversely proportional and there should be a negative correlation between them, error is linearly proportional with task difficulty and there should be a positive correlation between them.

Accordingly, the correlation results given in Table 1 were consistent with our expectations, except for surface-hit. While a strong ''negative'' correlation was observed between, the sole success measure in this study, the average target-hit scores and task levels ($r = -0.989$, $p < 0.01$), strong ''positive'' correlations were observed for the averages of the error measures, Miss scores ($r = 0.979$, $p < 0.01$) and friendly hit scores ($r = 0.963$, $p < 0.01$). The correlation between surface-hit scores and task levels was ($r = -0.61$, $p > 0.05$) not significant. Surface-hit did not significantly correlated with the changing task difficulty for the task, but it still indicated a lower cognitive load for participants.

Moreover, as the primary success and error measures, the ANOVA results of Target-hit and Miss particularly indicated an almost clear effect of changing task difficulty on the participants' performance. While Target-hit scores exhibited an inversely proportional relation with task difficulty, Miss scores exhibited a linearly proportional relation. Surprisingly, significant differences could not be obtained between level pairs 12–8 and 4–0 for Miss. Levels 12–8 and 4–0 may thus bring identical workloads to participants. We believe that this can be valid for 12–8, but we propose that this is not the case for 4–0 pair for the following reason.

Surface-hit results suggested that during level 0, (the easiest level) participants exhibited highly inattentive behavior. Although they were motivated not to make surface clicks before the task, Fig. 5d indicates that participants made many surface-hits on average at level 0. We believe that this is due to the fact that unoccupied cognitive capacity enables user attention to be distracted and task performance to degrade (Roda & Thomas, 2006). Therefore, when a task is too easy for a user, as in level 0, it leads to a low cognitive load, low engagement and decreased performance. Friendly hit results, conversely, partially fulfilled our expectations such that there were only statistically significant differences between level pairs 12–0 and 0–16 (Fig. 5d). This result indicated that the task used might have a forcing effect but did not cognitively overload all participants. Overall, one can conclude that the task in the experiment provided a reasonably valid base for the rest of the study.

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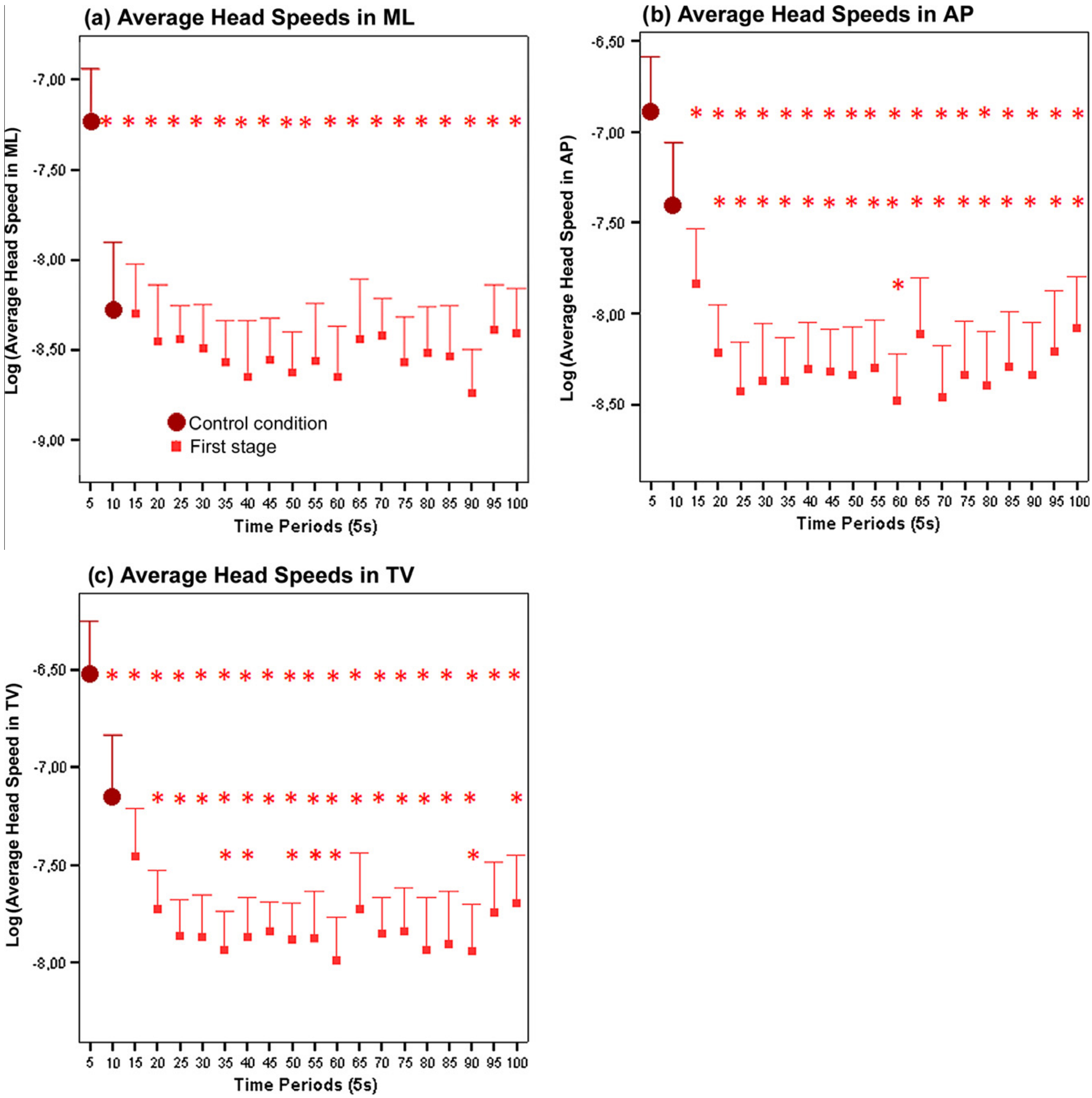

Fig. 7. Averages of head speed for 5-s time periods. Error bars indicate 95% confidence intervals. * indicates significance levels $p < 0.05$ or $p = 0.005$.

Table 1
Results of the correlation analysis run between averages of performance measures and task levels.

	Difficulty/Level	Target-hit	Friendly hit	Surface-hit	Miss
Difficulty/Level	1	−.989**	.963**	−.641	.979**
Target-hit	−.989**	1	−.965**	.701	−.950*
Friendly hit	.963**	−.965**	1	−.750	.903*
Surface-hit	−.641	.701	−.750	1	−.475
Miss	.979**	−.950*	.903*	−.475	1

The data showed no violation of normality (tested by the Shapiro–Wilky normality test).
* indicate that correlation is significant at the 0.01 level (2-tailed).
** indicate that correlation is significant at the 0.05 level (2-tailed).

5.2. Head movements

Task engagement is one of the key elements in this study. From a general point of view, engagement is described as "the connection between person and activity", reflecting a person's active involvement in a task or activity (Appleton, Christenson, Kim, & Reschly, 2006). Matthews et al. (2002) define task engagement as "effortful striving directed toward task goals".

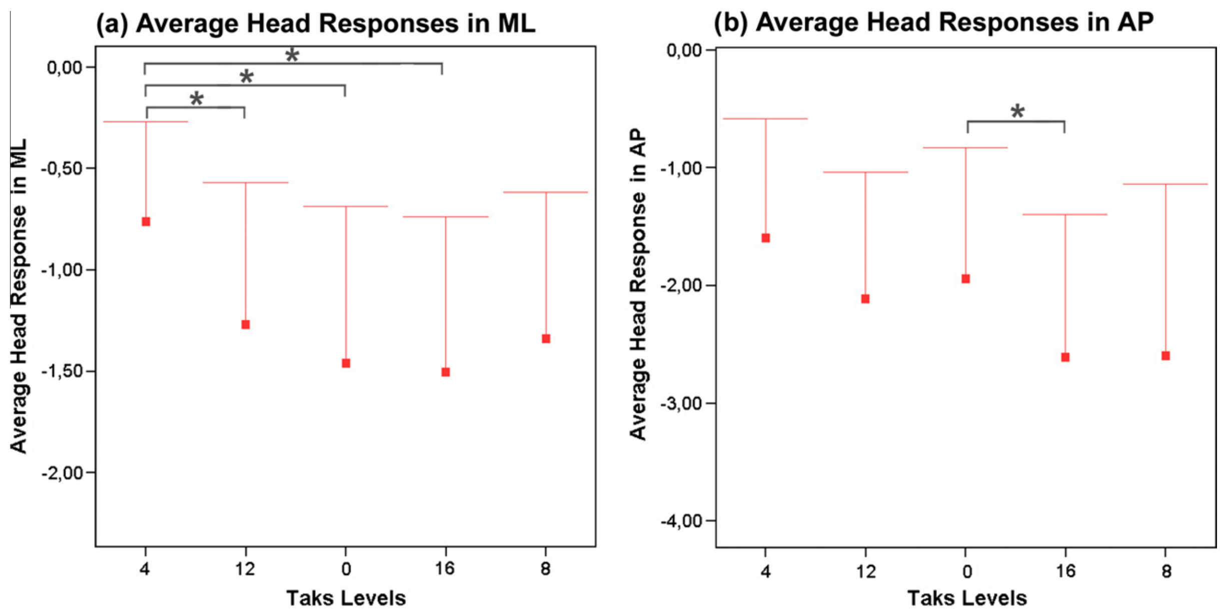

Fig. 8. Average head responses for task levels in ML and AP axes. * indicates significance levels $p < 0.05$. Error bars indicate 95% confidence intervals.

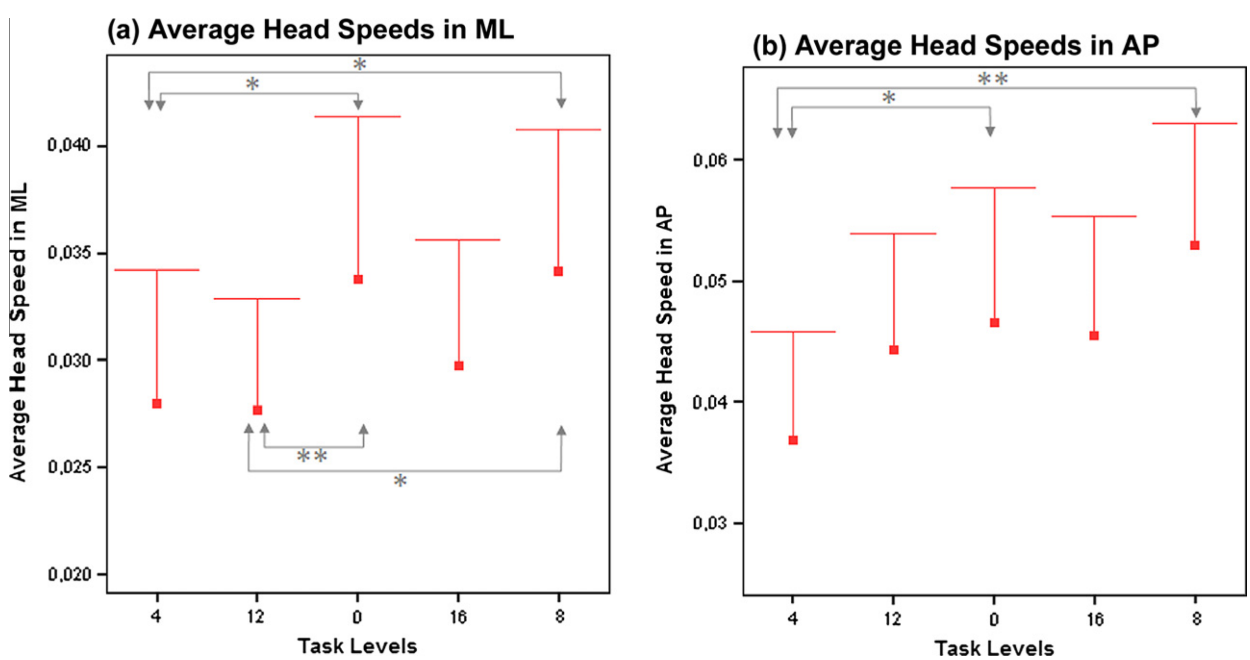

Fig. 9. Average head speeds for task levels in the ML and AP axes. Error bars indicate 95% confidence intervals. * and ** indicates significance levels $p < 0.05$ and $p < 0.005$, respectively.

Task engagement is a multidimensional concept incorporating three psychological dimensions, including cognition, motivation and affect (Fairclough et al., 2009). In other words, when a user engaged with the task, from the beginning to the end of the task, his or her engagement is primarily shaped by cognitive, motivational and affective factors. Task engagement can therefore be separately considered with respect to users' cognitive activity (mental effort), motivational orientation (approach vs. avoidance) and affective changes (positive vs. negative valance) (Fairclough et al., 2009). This means that each can separately affect user's engagement with the task and indirectly shape users' associated behaviors.

In this study, we focused on cognitive dimension of task engagement or cognitive engagement and its effects on users' involuntary head movements, head response and speed. We aimed to observe the effect of task engagement, changing task difficulty on participants' head movement behaviors by imposing a cognitive task with varying difficulties. The results indicated that head response and speed exhibited meaningful patterns resulting from task engagement and changing task difficulty.

Particularly, in the anterior/posterior (AP) axis, participants leaned forward or got close to the computer monitor (place where they directed their focus of attention) when the first stage of the task started, compared to the control condition, at a magnitude of approximately 16 mm. This is in alignment with previous research (Bahr et al., 2007; Balaban et al., 2004; Balaban et al., 2005; Frank, 2006) (discussed in Section 2.4), stating that cognitive engagement generates the needs to orient towards event or objects of priority and importance interest or humans exhibits cognitive engagement in orienting movements. In these studies, the authors report that participants close in computer monitor as a result of increasing task difficulty or increasing number of aircrafts during the first half of the wave. Our results in the AP axis indicate a similar effect and these validate the hypothesis that head response in the AP axis can be a global measure of cognitive engagement. Since, Abe and Makikawa (2009) noted that humans use eye and head movements to set visual attention area efficiently, we therefore alternatively suggest that closing into computer monitor can be due to the need to see better for increased performance through narrowing down the visual span and increasing the visual acuity.

In the medial/lateral (ML) axis, however, head response results indicated that participants leaned to the left during the control condition and the first stage (level 4) of the task at a small magnitude (1–10 mm). Fig. 8a shows that after the first stage of the task, participants did not make a displacement in that range in the ML axis. There is a statistically significant difference between the average head response in first stage and almost all the other stages (levels 12, 0, 16) which points that participants held their mean positions in the ML axis after the first stage. These results can be considered as an interesting supporting task engagement cue for such a monitor-oriented task. Task factors affect one's posture as discussed in Section 2.1. Since the task in the experiment required heavy mouse interaction, it seems that, when participants engaged with the task, their right arm continuously pressed on the table and it provided a stationary base for their body on the wrist.

Head movement results obtained in ML and AP axis, on the other hand, indicated that participants' heads slowed down in both axes as a result of task engagement. When analyzed in the transverse plane (TV) plane, this effect is commonly observed. Fig. 7c shows the continuous reduction in head speed even after the first 5 s of the first stage of the task (level 4). These can be interpreted as participants becoming more stationary to achieve the stability needed to attend to the computer display as they engaged with the task. Therefore we believe that head speed can be considered as a cue or measure of global task or cognitive engagement as well.

In terms of task difficulty, the results indicated a limited sensitive behavior to changing task difficulty for head response and speed. In the ML axis, participants stayed on a plateau in after the first stage of the task. After they engaged with the task, they kept their position even if there was change in difficulty during consecutive stages. Though this behavior can be considered an additional indicator of task engagement, as discussed above, it does not indicate a meaningful effect for head response in the ML axis as a result of changing task difficulty.

Head responses in the AP axis indicated that the effect of changing task difficulty on head response was limited such that a meaningful pattern was only observed in the AP axis when there was a major increase in task difficulty. Orienting movements are known as an indicator of cognitive resource allocation to events (Bahr et al., 2007). We therefore expected participants head to get close or move away from the monitor as result of changing task difficulty. However, a meaningful pattern was only observed in the AP axis when there was a significant increase in task difficulty.

Conversely, head speed results in the AP axis and more clearly in the ML axis indicated an inversely proportional relationship between task difficulty and head speed. Whenever the task difficult decreased, at level 0 after level 12 and at level 8 after 16, an obvious increase in head speed was observed. This shows that participants become less stationary when they perceive easiness in task difficulty. However, this effect was not sensitive to small changes in task difficulty such that there were no statistically significant differences between levels 4 and 12, and levels 16 and 8. Surprisingly, these was no a significant relation between level 0 and 16.

We speculate that both the general insensitive behavior obtained for changing task difficulty and specifically level 0 and 16 can stem from the decreasing engagement of participants after the third stage (level 0) of the task, due to a couple of reasons for this. In general, when a task is too difficult, too long or monotone or cause visual fatigue, these may cause users to lower their engagement with the task. Accordingly, level 16 could be too difficult for some participants but not all, task duration could be too long and cause participants to be bored or experience visual fatigue. We believe that in future studies, these should be carefully considered in experimental designs.

There is not a direct study to compare the task difficult analysis results in previous research, but Frank (Frank, 2006) report an increasing stability in torso movements as a result of task difficulty. Yet, head movements are also related to human sight and visual attention and their movements can be free from torso movements, participants could move their head for visual purposes affecting head stability. Therefore, we believe that such a stability exhibited in torso movements should not be expected in head movements.

In conclusion, the task difficulty analysis results suggested head response and speed as supplementary measures of task difficulty and cognitive load. These measures may not be directly suitable for applications that require a certain level of precision in cognitive load assessment. Although the results indicated a limited sensitivity behavior and suggest head movement as a long-term or global cognitive load measure, further investigations are needed to better understand this relation and its use in Attentive Computing Systems (ACSs).

A comparative task analysis must be performed using multiple different tasks in order to be able to assess generalized head movement response against various task types, enabling a development of a possible statistical scale. However, in areas, where strong precision is not sought, such as intelligent TV sets or commodity computers, user engagement and cognitive load can be predicted through head movements without advanced hardware. We strongly believe that just as humans observe each other in personal communication interactions, computers should observe humans as well and behave accordingly.

6. Conclusions

Posture is a multidimensional construct that can express users' voluntary and involuntary motivations and purposes. It, statically or dynamically, as a whole or by its parts, provide significant means for modern (user sensitive and adaptive) Human Computer Interaction (HCI) paradigms, such as Attentive Computing Systems (ACSs). Particularly, automatic motor behaviors or involuntary postural responses of users have significant potential to meet the needs of ACSs, as both standalone and supplementary measures of cognitive state and more suitable to be utilized in real environments.

However, this potential requires further investigation on the basis of humans' postural control system, nonverbal communication principles, event perception and characteristics of attentional and cognitive mechanisms. In order to exploit this potential, this paper investigated seated users' involuntary postural responses and head movements correlated with cognitive changes as input for ACSs. The paper has two main contributions.

The first is an introduction that reviews seated users' involuntary postural responses from a cognitive state assessment perspective. This introduction integrates and discusses various related topics from different disciplines and different fields of Human Computer Interaction (HCI), including posture, seated posture, its advantages for and connections with cognitive state assessment, origins of cognitively meaningful postural changes and related studies.

As the second main contribution, the paper empirically examines involuntary head movements of seated users correlated with cognitive changes using the summary measures of head response and speed. The results indicated that head response and speed exhibited meaningful patterns resulting from task engagement. While these strengthen the hypothesis that head response serves as a tonic measure of task or cognitive engagement, they also suggest head speed as a novel and overall cognitive engagement measure.

The effect of changing task difficulty, conversely, partially satisfied our initial expectations. Although they responded changing task difficulty to certain extent, head speed and, more clearly, head response were not sensitive to small changes in task difficulty. We believe that the limited sensitive behavior of head movements to task difficulty or cognitive load observed in this study may stem from the characteristics of task used or task factors. Ergonomics studies emphasize that task factors, particularly the visual demands of a task, influence seated posture. Further investigations with different tasks and experimental procedures are therefore required to better understand the relation between head movements and cognitive load.

The assessment of users' cognitive engagement and workload using the involuntary head movements provide several implications for both ACSs and other fields of HCI. Measures of user attention are of great importance for ACSs and the literature suggests head direction and eye-gaze as good indicators of users' attention to objects or people since humans look at what they focus on in most cases (Vertegaal et al., 2006; Zhai, 2003). However, humans looking at an object or person constitute good examples of visual interest but not necessarily cognitive interest (Vertegaal, 2002). To determine whether the information has been mentally processed, additional information is required. We believe that orienting movements and increasing head stability can provide this information and serve as indicators of cognitive interest.

Moreover, since ACSs aim a natural and unobtrusive communication with users, these systems need to determine users' interruptibility or availability to communication. Interruptibility is a concept closely related to users' engagement and mental workload, as well as other dimensions of users' mental states. Therefore, an ACS can use involuntary head movements to infer users' interruptibility level. For instance, while a high engagement or workload state may be an inopportune moment to interrupt a user, low engagement and workload moments can be exploited as opportune moments to communicate with user.

The head movement behaviors reflecting cognitive engagement and workload presented in this study can be used to design attentive and more natural embodied or virtual agents and robots. These systems, similar to ACSs, require to unobtrusively communicating with users, in a variety of different settings from museums to laboratories. Additionally, since these systems interact with users more like a human than a machine, users' acceptance of an agent or a robot as a partner, colleague or assistant is quite important for efficient communication (Morency et al., 2007; Yamaoka et al., 2009). Therefore, these systems, as well as attentively regulating their communications with users, need to behave like humans during conversations. The results of this and other similar studies provide the necessary information for these systems to conduct a human like interaction with users by mimicking the presented overt behaviors of humans.

The level of users' cognitive engagement or workload provides various paths for different research and applications areas related HCI. We can describe these, as areas that will aim to optimize user performance with different purposes, including game research, education and life critical systems. Particularly users' cognitive engagement is quite valuable for such areas, since the level of users' cognitive engagement directly affects his or her performance, being also an indicator mental overload, boredom and fatigue. This is due to the fact that humans may tend to lower their engagement as a result of excessive task difficulty, monotony of the task and visual fatigue (Fairclough et al., 2009; Matthews et al., 2002). In all cases, a low engagement will negatively affect both the performance of users and systems, and eventually the intended benefit of the systems both for users and vendors.

In game research, determining users' cognitive engagement can significantly enhance gaming or entertainment experience. Games can be designed in a manner to keep users' engagement high with the game, by manipulating game difficulty in response to users' measured engagement and workload.

Student engagement is of particular importance in education, since it highly affects student achievement and provides opportunities to determine the time and type of necessary interventions to instructors or instruction system (Appleton et al., 2006). For instance, if an instructional computing system can actively monitor student engagement, the information can be utilized to attract student's attention and reengage them to the course if necessary.

In life critical interactive systems, including aviation monitoring, driving, flying, military system control, etc., keeping operators' performance above a certain level is extremely important, as any impaired performance can cause both huge monetary and life losses (Balaban et al., 2004). We believe that by monitoring cognitive engagement and holding it above a proper level by applying necessary interventions, both the performance of the operator and systems can be saved before indications of actual performance degradation starts to occur. This can include signaling operation administrators, when a risk is detected in the operator engagement level or preempt from the task completely.

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