Cognition-Aware Computing

Andreas Bulling, *Max Planck Institute for Informatics*
Thorsten O. Zander, *Technical University of Berlin*

Context-aware computing systems aim to proactively help users by automatically sensing the context and adapting system behavior to address users' needs and expectations. The context can comprise personal factors—such as physical activity, social interactions, and the psychophysiological or affective state—as well as environmental factors—such as location and the surrounding infrastructure. The problem of inferring and analyzing affective states has attracted considerable research interests in recent years and has been investigated thoroughly in affective computing. In contrast, sensing and analyzing processes of cognition has received relatively little attention, despite the fact that such processes hold considerable potential for context-aware computing.

When a user interacts with a computing system, the ability to sense cognition would let the system identify the different aspects of mental information processing—such as engagement, cognitive load, memory, knowledge, and learning (see Figure 1). If we could measure these aspects as additional contextual cues in daily life, it would add a cognitive dimension to the current notion of context, paving the way for cognition-aware computing systems.

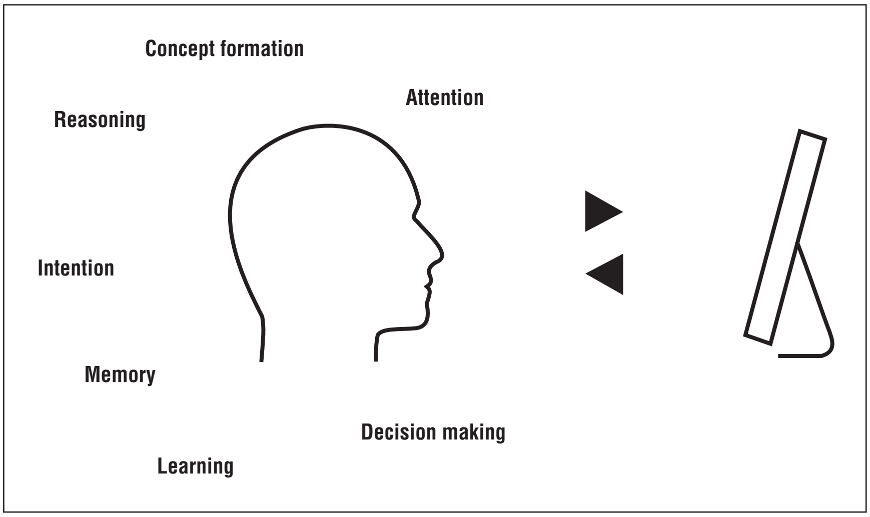

Figure 1. Cognition-aware computing systems and interfaces sense and adapt to covert aspects of the user state—the so-called cognitive context. The computer directly assesses information about the users' cognitive state without any direct communication from the user to the system. This information is used to refine the ongoing interaction—for example, through automated adaptation.

CHALLENGES IN COGNITION AWARENESS

We define a computing system as cognition aware if it senses and adapts to cognitive aspects of the personal context—the so-called *cognitive context,*[1] also referred to as covert aspects of the user state.[2] Cognition awareness allows for novel applications, such as ensuring an optimal game experience by dynamically adjusting game demands according to engagement or immersion.[3] Other examples include providing information about forgotten people or places by assessing the success or failure of memory-recall processes,[4] or supporting people during safety-critical tasks by monitoring cognitive workload and fatigue.[5]

Current context-aware systems, however, face several challenges in trying to obtain the cognitive context in an unobtrusive manner—using, for example, sensors attached to the human body or placed in the environment. First, similar to affective computing, the cognitive context often is encoded in complex neural dynamics of brain activity, and only a few obvious cues are accessible by noninvasive measurement techniques. This is in contrast to other contextual cues, such as physical activity, that can readily be sensed from body movements using on-body inertial sensors. Sensors that are commonly used to measure brain activity, such as functional magnetic resonance imaging (fMRI), require bulky or sensitive equipment that's not well suited or robust enough for mobile daily-life recordings.

Published by the IEEE CS ■ 1536-1268/14/$31.00 © 2014 IEEE

WEARABLE SENSING SOLUTIONS FOR VISUAL BEHAVIOR AND EEG

Head-mounted eye trackers can be distinguished by the measurement technique they use. The two most widely used techniques today are electrooculography (EOG) and video. EOG is an electrode-based technique that measures changes in the electrical potential field around the eyes, caused by eye movements. EOG is computationally lightweight and can be implemented as a real-time, low-power wearable system, but it's sensitive to noise and can only track relative eye movements with high temporal resolution.[1]

Video-based eye trackers are the current standard in research and industry because they can provide accurate 2D and 3D gaze estimates. They rely on a combination of infrared illumination of the eye, high-resolution cameras, and computer vision techniques for pupil detection and tracking. On the downside, video-based eye tracking is computationally expensive and sensitive to ever-changing lighting conditions in outdoor environments.

Although commercial head-mounted eye trackers are still expensive and therefore only used by specialized user groups, efforts to make eye tracking accessible to the general public led to the development of open source alternatives, such as the Pupil open source eye-tracking platform (see Figure A1).[2]

Electroencephalography (EEG) systems measure changes in electrical activity at the scalp. Typically, 32 to 256 electrodes are connected to the skin using a conductive gel to reduce impedance. Setting up a standard EEG cap is time-consuming, the cap is cumbersome to wear, and users have to deal with gel in their hair. These are the main reasons why passive BCIs haven't yet appeared in many real-world applications. Recent advances in dry electrode EEG systems can measure brain activity without using gel. Although they're still cumbersome to wear, the set-up time is only approximately five minutes.

First high-density wearable EEG headsets are available now (see Figure A2) that will pave the way for assessing the cognitive context with passive BCI systems.[3] In addition to usable acquisition hardware, passive BCIs also rely on software to extract features representing correlates of (covert) aspects of cognition. Several open source toolboxes, such as BCILAB,[4] are available for this task.

(1) (2)

Figure A. Head-mounted sensing modalities. The first is an eye-tracker the second an EEG system: (1) The Pupil open source platform for pervasive eye tracking and mobile gaze-based interaction by Pupil Labs in Berlin, and (2) the wearable 64 channel dry electrode EEG head cap from Cognionics in San Diego.

REFERENCES

1. A. Bulling, D. Roggen and G. Tröster, "EyeMote—Towards Context-Aware Gaming Using Eye Movements Recorded From Wearable Electrooculography," *Proc. 2nd Int'l Conf. Fun and Games* (FnG 08), 2008, pp. 33–45.
2. M. Kassner, W. Patera, and A. Bulling, "Pupil: An Open Source Platform for Pervasive Eye Tracking and Mobile Gaze-Based Interaction," 2014; http://arxiv.org/abs/1405.0006.
3. T.O. Zander et al., "A Dry EEG-System for Scientific Research and Brain–Computer Interfaces," *Frontiers in Neuroscience*, May 2011, article no. 53.
4. A. Delorme et al., "MATLAB-Based Tools for BCI Research," *Brain-Computer Interfaces*, Springer, 2010, pp. 241–259.

A second challenge relates to the experimental methodology used. When assessing the cognitive context, specific cognitive processes first must be evoked and measured reliably in controlled settings and then robustly inferred in complex daily life situations. In addition, co-occurring cognitive factors must be carefully isolated. This requires a multidisciplinary approach at the crossroads of cognitive sciences, psychology, machine learning, and engineering.

Finally, linking subtle cues in sensor signals to cognitive processes requires domain-specific modeling and inference techniques. In the simplest case, this would involve combining and adapting existing methods from pattern recognition and machine learning for this new problem domain. However, research on cognition awareness will also require and drive the development of new computational methods geared toward cognitive context evaluation.

PROMISING SOLUTIONS

Considerable potential for cognition-aware computing lies in two sensing modalities that have long been used in other fields but have not been fully exploited to infer the cognitive context yet—visual behavior and portable electroencephalography (EEG). Human visual behavior, measured using mobile or stationary eye trackers, has a long history as a tool in clinical ophthalmology, experimental psychology, and human-computer interaction. Recent advances in mobile eye-tracking equipment point the way toward unobtrusive systems for monitoring and analyzing visual behavior pervasively in everyday life.[6] (For more information, see the sidebar.)

Similarly, EEG has found significant use in active but more recently

WEARABLE COMPUTING

also passive brain-computer interfaces (BCI)[7] and has become an important tool for real-time analysis of brain activity. The unique characteristic of visual behavior and passive BCIs is that both are closely linked to human cognition and thus potentially provide rich information about the cognitive context. For this reason, both modalities are often called a window into the mind.[8] Previous works by us and other members of the research community suggest that visual behavior and passive BCIs might hold the key to accessing at least part of the cognitive context, making it accessible to cognition-aware computing.

Visual Behavior Analysis

In experimental psychology, a large body of work identifies eye movement characteristics that are linked to cognitive processes. For example, studies show that our eyes follow certain paths depending on what task we perform or have in mind[9] and that eye movements correlate with the type of memory access required to perform these tasks.[10] Other findings suggest that eye movements are good measures of perceptual learning and experience,[11] visual search,[12] and fatigue.[13] Significant differences in eye movement patterns were also found for people looking at familiar versus unfamiliar faces.[14]

In pervasive computing, researchers only recently identified visual behavior as a contextual cue and started to analyze eye activity—that is, eye movements during daily tasks in natural environments, in a similar fashion as physical activity. Specifically, research conducted by us and colleagues showed that a variety of visual and nonvisual activities can be spotted and recognized automatically from visual behavior, such as office activities,[15] concentrated work,[16] or reading.[17] All of these findings demonstrate the significant information content available in eye movements for assessing user context. In contrast, analysis and inference of the cognitive context still remains relatively unexplored. Work in this area has thus far focused on inferring visual memory recall,[4] intention,[18] or language expertise[19] from eye movements.

Passive Brain-Computer Interfaces

Since their introduction, passive BCIs have been used to track changes in users' brain activity. For example, a 70 percent detection rate has been achieved for detecting the intention to press a key, even before the onset of any muscular activity. Similarly, other work has shown that bluffing during a dice game could be detected with an accuracy of 80 percent (a review of these studies appears elsewhere[7]). Previous work also investigated users' perception of errors during interaction with a technical system.[20] Both user errors as well as system errors—for example, if the system didn't properly adapt to the user—could be detected and corrected with a reliability of up to 80 percent for users errors and 85 percent for system errors. Such error detections could be used for implicit control—that is, interaction with a computing system without explicit input from the user. Instead, such a system could monitor the user during the interaction and use this information to automatically adapt its behavior to the user's goals and strategies.[21]

Unity is Strength

What makes both modalities even more promising for cognitive context evaluation is that contextual information obtained from one modality complements that derived from the other. Visual behavior reflects the cognitive processes that elicited it and can therefore be seen as the external manifestation of the cognitive context. Therefore, by analyzing visual behavior, changes in cognitive context can be inferred.[6] Passive BCIs complement the information obtained from visual behavior analysis by providing insights into the internal manifestation of the cognitive context, which could be assessed by measuring brain activity.[2]

One recent work demonstrated this beneficial combination of visual behavior analysis and passive BCI. In gaze-based interaction, items are often selected by dwelling on them for a certain amount of time. This overt attention can be derived directly from gaze behavior but suffers from the so-called Midas Touch problem—erroneous selections because users also dwell on other parts of the screen and with different intents. Previously blinks or eye gestures were used to indicate selections, in an attempt to resolve the Midas touch problem. Janna Protzak and her colleagues presented a different solution using cognitive context. They directly inferred the selection intent from brain activity to confirm dwell-time-based gaze selection.[22] This study is thus a first proof of principle that a combination of gaze analysis and passive BCI provides better insight into cognitive context.

These initial studies demonstrate the considerable potential of analyzing the cognitive context for context-aware computing. Eye movement analysis and passive BCIs hold great promise for investigating the cognitive context of a person in daily life situations. We strongly believe that a combination of both measurement techniques will pave the way for a new genre of wearable and pervasive computing systems that use the cognitive dimension for context awareness.

Despite their significant potential, developing cognition-aware systems requires addressing a number of technical challenges with respect to system design and behavior. How does a cognition-aware environment or interaction with cognition-aware objects need to be designed and implemented? Which feedback is most appropriate to react to changes in the cognitive context of a person? Answers to these and similar questions will open up new areas of research, particularly in HCI and design.

In addition to the technical challenges, the rise of cognition-aware systems will also lead to ethical and privacy issues. How will cognition-aware computing influence our daily lives? What are the broader implications on society and politics if people use systems that can "read their mind"? Should access to the cognitive context be restricted? Or should it be shared—for example, to help autistic people or people from different cultural backgrounds? Either way, extending the information base accessible by computer systems to include cognitive context will have a significant impact on future human-computer interaction.

REFERENCES

1. A. Bulling, D. Roggen and G. Tröster, "What's in the Eyes for Context-Awareness?" *IEEE Pervasive Computing*, vol. 10, no. 2, 2011, pp. 48–57.
2. T.O. Zander and S. Jatzev, "Context-Aware Brain–Computer Interfaces: Exploring the Information Space of User, Technical System and Environment," *J. Neural Eng.*, vol. 9, no. 1, 2012, no. 016003.
3. A. Nijholt, and D. Tan, "Playing with your Brain: Brain-Computer Interfaces and Games," *Proc. Int'l Conf. Advances in Computer Entertainment Technology* (ACE 07), 2007, pp. 305–306.
4. A. Bulling and D. Roggen, "Recognition of Visual Memory Recall Processes Using Eye Movement Analysis," *Proc. Ubiquitous Computing* (UbiComp 11), 2011, pp. 455–464.
5. C.A. Kothe and S. Makeig, "Estimation of Task Workload from EEG Data: New and Current Tools and Perspectives," *Proc. Eng. Medicine and Biology Society* (EMBC 11), 2011, pp. 6547–6551.
6. A. Bulling and H. Gellersen, "Toward Mobile Eye-Based Human-Computer Interaction," *IEEE Pervasive Computing*, vol. 9, no. 4, 2010, pp. 8–12.
7. T.O. Zander and C. Kothe, "Towards Passive Brain–Computer Interfaces: Applying Brain–Computer Interface Technology to Human–Machine Systems in General," *J. Neural Eng.*, vol. 8, no. 2, 2011, no. 025005.
8. B.M. Velichkovsky and J.P. Hansen, "New Technological Windows into Mind: There Is More in Eyes and Brains for Human-Computer Interaction," *Proc. SIGCHI Conf. Human Factors in Computing Systems* (CHI 96), 1996, pp. 496–503.
9. M.F. Land, "Eye Movements and the Control of Actions in Everyday Life," *Progress in Retinal and Eye Research*, vol. 25, no. 3, 2006, pp. 296–324.
10. D. Melcher and E. Kowler, "Visual Scene Memory and the Guidance of Saccadic Eye Movements," *Vision Research*, vol. 41, nos. 25–26, 2001, pp. 3597–3611.
11. M.M. Chun, "Contextual Cueing of Visual Attention," *Trends in Cognitive Sciences*, vol. 4, no. 5, 2000, pp. 170–178.
12. S.P. Liversedge and J.M. Findlay, "Saccadic Eye Movements and Cognition," *Trends in Cognitive Sciences*, vol. 4, no. 1, 2000, pp. 6–14.
13. R. Schleicher et al., "Blinks and Saccades as Indicators of Fatigue in Sleepiness Warnings: Looking Tired?" *Ergonomics*, vol. 51, no. 7, 2008, pp. 982–1010.
14. J.J. Heisz and D.I. Shore, "More Efficient Scanning for Familiar Faces," *J. Vision*, vol. 8, no. 1, 2008, pp. 1–10.
15. A. Bulling et al., "Eye Movement Analysis for Activity Recognition Using Electrooculography," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 33, no. 4, 2011, pp. 741–753.
16. B. Tessendorf et al., "Recognition of Hearing Needs from Body and Eye Movements to Improve Hearing Instruments," *Proc. Pervasive 2011*, 2011, pp. 314–331.
17. K. Kunze et al., "The Wordometer—Estimating the Number of Words Read Using Document Image Retrieval and Mobile Eye Tracking," *Proc. 12th Int'l Conf. Document Analysis and Recognition* (ICDAR 13), 2013, pp. 25–29.
18. R. Bednarik, H. Vrzakova, and M. Hradis, "What Do You Want to Do Next: A Novel Approach for Intent Prediction in Gaze-Based Interaction," *Proc. Symp. Eye Tracking Research and Applications* (ETRA 12), 2012, pp. 83–90.
19. P. Martínez-Gómez and A. Aizawa, "Recognition of Understanding Level and Language Skill Using Measurements of Reading Behavior," *Proc. 19th Int'l Conf. Intelligent User Interfaces* (IUI 14), 2014, pp. 95–104.
20. P. Ferrez and J.D.R. Millán, "You Are Wrong! Automatic Detection of Interaction Errors from Brain Waves," *Proc. 19th Int'l Joint Conf. Artificial Intelligence* (IJCAI 05), 2005, pp. 1413–1418.
21. T.O. Zander et al., "Towards BCI-Based Implicit Control in Human–Computer Interaction," *Advances in Physiological Computing*, Springer, 2014, pp. 67–90.
22. J. Protzak, K. Ihme, and T.O. Zander, "A Passive Brain-Computer Interface for Supporting Gaze-Based Human-Machine Interaction," *Proc. 7th Int'l Conf. Universal Access in Human-Computer Interaction: Design Methods, Tools, and Interaction Techniques for eInclusion* (UAHCI/HCII 13), 2013, pp. 662–671.

Andreas Bulling is head of the Perceptual User Interfaces Group at the Max Planck Institute for Informatics and the Cluster of Excellence on Multimodal Computing and Interaction at Saarland University, Germany. Contact him at bulling@mpi-inf.mpg.de.

Thorsten O. Zander is a senior postdoctoral researcher at the Technical University of Berlin, where he leads the Team PhyPA. Since 2009, he has also been a research affiliate at the Swartz Center for Computational Neuroscience at the University of California San Diego. Contact him at tzander@gmail.com.