What's in the Eyes for Context-Awareness?

Eye movements are a rich source of information about a person's context. Analyzing the link between eye movements and cognition might even allow us to develop cognition-aware pervasive computing systems that assess a person's cognitive context.

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Context-awareness has emerged as a key area of research in mobile and pervasive computing. In addition to location, physical activity is one of the most important contextual cues.[1] In the last decade, a large body of research in activity recognition has addressed various problem domains and applications. Ambient sensors such as video cameras, reed switches, or sound can recognize physical activity in indoor environments. In mobile settings, body-worn sensors can help detect physical activity. Because body movements are directly related to a person's physical activities, motion sensing is typically performed using accelerometers or gyroscopes.

A rich source of information on context that has not been used so far is the movements of the eyes. The dynamics of eye movements as we engage in specific activities reveal much about the activities themselves (for example, reading). Similarly, specific environments or locations influence our eye movements (for example, while driving a car).

Finally, eye movements are strongly related to the cognitive processes of visual perception, such as attention, visual memory, or learning. In addition to physical activity or location, eye movement analysis could help us infer these processes in real-world settings. Eventually, this might let us extend the current notion of context with a cognitive dimension, leading to cognition-aware systems that enable novel types of user interaction not possible today.

Tracking Eye Movements

If we are to infer context from eye movements, we must first track these movements. Several well-known tools to track gaze direction exist, particularly in the field of human–computer interaction (HCI). Stationary video-based eye trackers are widely available and extensively used in various commercial applications. For example, in 2006 Toyota presented a driver-monitoring system that analyzed gaze direction to warn car drivers if they were not paying attention to the road. Tobii Technology (www.tobii.com) sells eye trackers for use in market research and usability studies to analyze what attracts customers' attention and to optimize product placement or improve website design.

Research in eye-based HCI has traditionally focused on direct manipulation of user interfaces using gaze tracking in stationary settings. For example, gaze has been successfully used as computer input[2] and for interactive trip planning for tourists.[3] A growing number of researchers investigate gaze direction in mobile daily life environments. Tracking eye movements in such settings is a much more difficult problem—mainly because the development of wearable eye trackers that are robust to physical activity and allow for long-term recordings is still an active field of research[4] (also see the "Sensing Solutions for Wearable Eye Tracking" sidebar).

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Sensing Solutions for Wearable Eye Tracking

The acquisition of eye movement data in daily life situations calls for highly miniaturized, low-power eye trackers with real-time processing capabilities. Commercial video-based systems increasingly address these requirements. Some of these systems, such as Applied Science Laboratories' Mobile Eye (www.asleyetracking.com) and SensoMotoric Instruments' iView X HED (www.smivision.com), target mobile users.

Efforts to miniaturize video-based eye trackers led researchers to consider alternative measurement techniques. Among these, electrooculography (EOG) is probably one of the more well known. Using electrodes attached to a person's skin around the eyes, EOG measures changes in the electric potential field caused by eye movements. By analyzing these changes, the system can track eye movements. Proposed mobile systems include headphones with integrated electrode arrays[1] and a head cap with EOG electrodes embroidered with silver-coated thread.[2]

We have demonstrated an EOG-based wearable eye tracker implemented as ordinary goggles.[3] This self-contained device uses dry electrodes integrated into the goggles' frame and a small pocket-worn component with a digital signal processor for real-time EOG signal processing. Onboard data storage and low-power design allow for more than seven hours of mobile data recording and online eye movement analysis (see Figure A).

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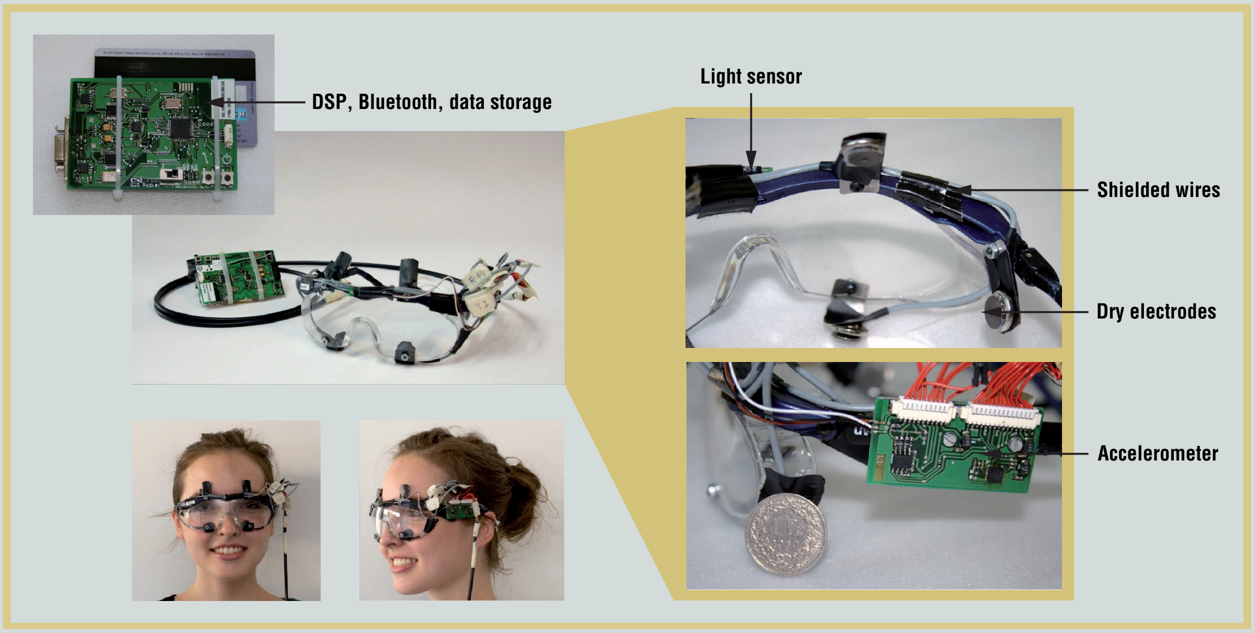

Figure A. Wearable electrooculography (EOG)-based eye tracker integrated into ordinary safety goggles. With onboard data storage and a low-power design, the tracker can work for more than seven hours, recording mobile data and analyzing eye movement online.

Eye Movement Analysis

The complementary, but also less common, approach to using gaze direction is to analyze the dynamics of a person's visual behavior over time. Eye movements can generally be categorized as conscious, unconscious, or a combination of the two.[5] Conscious eye movements are those we are most aware of; we use them to deliberately gaze at certain points of interest. Unconscious eye movements are generated by the oculomotor plant, a visual neural system in the brain. Most natural tasks involve an interaction

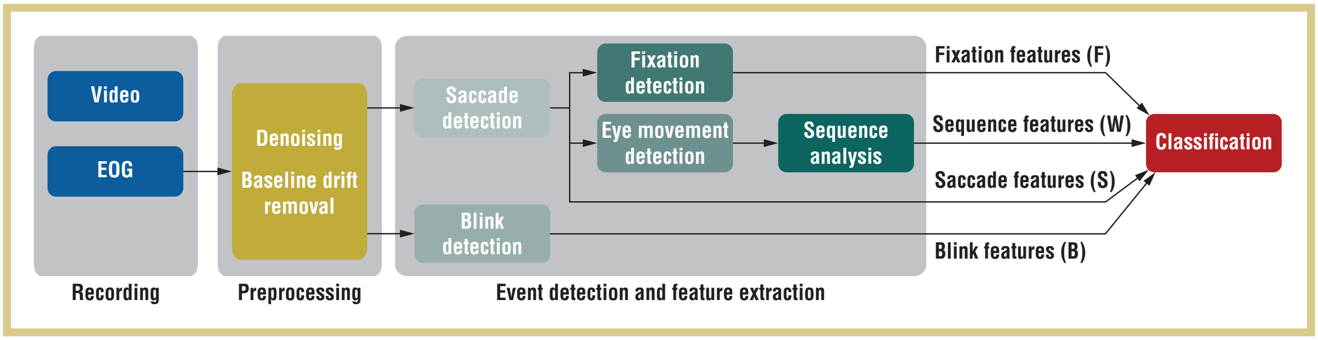

Figure 1. System architecture for eye-based context recognition. The system comprises modules for recording data using video-based eye tracking or electrooculography (EOG), signal preprocessing (details shown for EOG), as well as the detection of the main eye movement characteristics such as saccades, fixations, and blinks. The features extracted from these characteristics are finally used for classification.

between conscious and unconscious eye movements. For example, reading is a conscious visual activity but partially involves unconscious eye movements trained while acquiring reading skills.

Outside pervasive computing, eye movement analysis has a long history as a means of investigating visual behavior. For example, researchers found that analyzing the sequence of gaze points let them identify the most salient features in a picture (and thus those that attract an observer's attention).[6] Others showed that it is possible to support the training of novice doctors in assessing tomography images by modeling the visual behavior of domain experts based on the dynamics of their eye movements.[7] These studies are only two examples of many that analyzed and modeled eye movement characteristics during specific tasks. In pervasive computing, however, no one has yet used eye movement analysis for context recognition.

Context Recognition Using Eye Movement Analysis

We developed a recognition system that analyzes and models visual behavior and maps eye movements to a defined set of context classes. In a training phase, we record eye movements while a person experiences a situation of interest. During operation, we then compare eye movements to those observed during training to determine the most similar context class.

Figure 1 shows the architecture of our eye-based context recognition system. In the first stage, eye movement data is acquired using an eye tracker. Depending on application requirements, we can use different recording techniques, such as eye tracking based on video or electrooculography (EOG). In the second stage, the system preprocesses the data to remove any artifacts that might hamper eye movement analysis. This preprocessing directly depends on the particular recording technique. If we are using EOG signals, we typically employ denoising and signal drift removal. From the preprocessed eye movement data the system can detect different eye movement characteristics. These might include blinks, fixations, or saccades, or additional characteristics that cover specific aspects of eye movement dynamics. In practice, using these eye movement characteristics directly is challenging. Therefore, we rely on features calculated from these characteristics for classification (see the "Eye Movement Characteristics and Features" sidebar).

We applied this system in two case studies addressing different activity recognition problems in mobile and stationary settings.

Case Study 1: Reading Recognition

In the first case study, we investigated the problem of recognizing people reading while in transit in everyday environments (details are available elsewhere[8]). Reading is a truly pervasive activity. People read on computer screens at work, they read advertisements and signs in public, and they read books at home or while traveling. Thus, information about individuals' reading activity is a useful indicator of their daily situation as well as a gauge of task engagement and attention. For example, attentive user interfaces could comprise the current level of user interruptability or assist people with reading disabilities by automatically magnifying or explaining words or context in the text.

We defined a scenario of traveling to and from work. The experiment involved eight participants occasionally reading text during different modes of locomotion, including sitting at a desk, walking along a street, waiting at a tram stop, and riding a tram (see Figure 2a). We recorded their eye movements during reading using a wearable EOG system. Each participant was followed by an assistant who annotated both the current mode of locomotion and whether the participant was reading. To be able to detect whether the participant's eyes were on the page, the assistant had to monitor the participant from close proximity. To avoid

Eye Movement Characteristics and Features

To be able to use eye movement analysis for context recognition, it is important to understand the different types of eye movement. We identified six movement types that are potentially useful for context recognition. Currently, however, we rely on only three of them: saccades, fixations, and blinks (see Figure B for examples). For each movement type, we can extract different features that reflect eye movement dynamics (details on the signal processing required to extract these features are available elsewhere[1]).

Saccades

The eyes move constantly in saccades to build a mental map from interesting parts of the visual scene. The main reason for this is that only a small central region of the retina, the *fovea*, can perceive with high acuity. We extract a total of 62 saccadic features (S), such as the mean, variance, and maximum EOG signal amplitudes of saccades, and normalized saccade rates. We calculate all of these features for horizontal and vertical movement, for small and large saccades, for saccades in positive or negative direction, and for all combinations of these.

We also developed a wordbook-encoding scheme to analyze repetitive eye movement patterns. This scheme creates wordbooks that hold statistics on the occurrence counts and the type of all movement patterns of a particular length that occur in an eye movement dataset. For such a wordbook we used five features: the wordbook size, the maximum occurrence count, the difference between the maximum and minimum occurrence counts, and the variance and mean of all occurrence counts.

Fixations

A fixation is the eye's static state during which gaze is held upon a specific location. Humans typically alternate saccadic eye movements and fixations. For each fixation, we extract five fixation features (F): the mean and the variance of the EOG signal amplitude within the fixation; the mean and the variance of the fixation duration; and the fixation rate in the window.

Blinks

The frontal part of the cornea is coated with a thin liquid film, the *precornial tear film*. Spreading this lacrimal fluid across the corneal surface requires regular blinking. Environmental factors (for example, relative humidity, temperature, and brightness) influence the average blink rate, as do physical activity, cognitive workload, and fatigue. We extract three blink features (B): the blink rate, and the mean and variance of blink duration.

Microsaccades

Microsaccades are fast involuntary eye movements of small amplitude that occur during prolonged fixations. The role of microsaccades in visual perception is still a highly debated topic among human vision researchers. Typically, microsaccade amplitudes vary over only one to two minutes of arc.[2] Although microsaccades can be detected with recent video-based eye trackers, signal artifacts still prevent their detection using EOG.

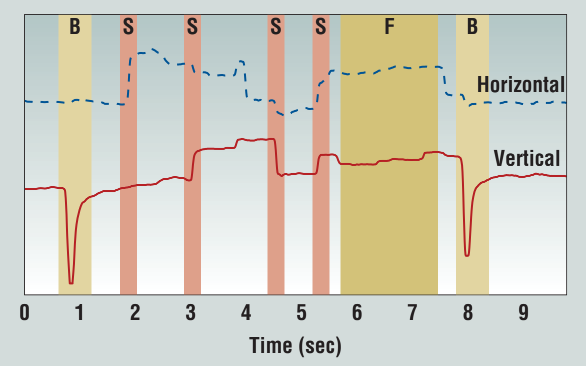

Figure B. Horizontal and vertical electrooculography (EOG) signals showing examples of saccades (S), fixations (F), and blinks (B). For each movement type, we can extract different features that reflect eye movement dynamics.

Vestibulo-Ocular Reflex

The vestibulo-ocular reflex (VOR) is a very fast eye movement triggered to stabilize gaze on a stationary object during head movements. The VOR compensates for these movements by moving the eye in the opposite direction of the head movement. The VOR is difficult to differentiate from saccades using only EOG—that is, without any information on head movements. So, we did not explicitly use eye movements caused by the VOR.

Smooth Pursuit Movements

Humans voluntarily perform smooth pursuit movements when stabilizing their gaze on a moving visual target. Psychological deficits that have noticeable effects on the velocity of smooth pursuit movements include schizophrenia, autism, and posttraumatic stress disorder. Because of similar signal characteristics, smooth pursuit movements are difficult to separate from EOG signal drift.

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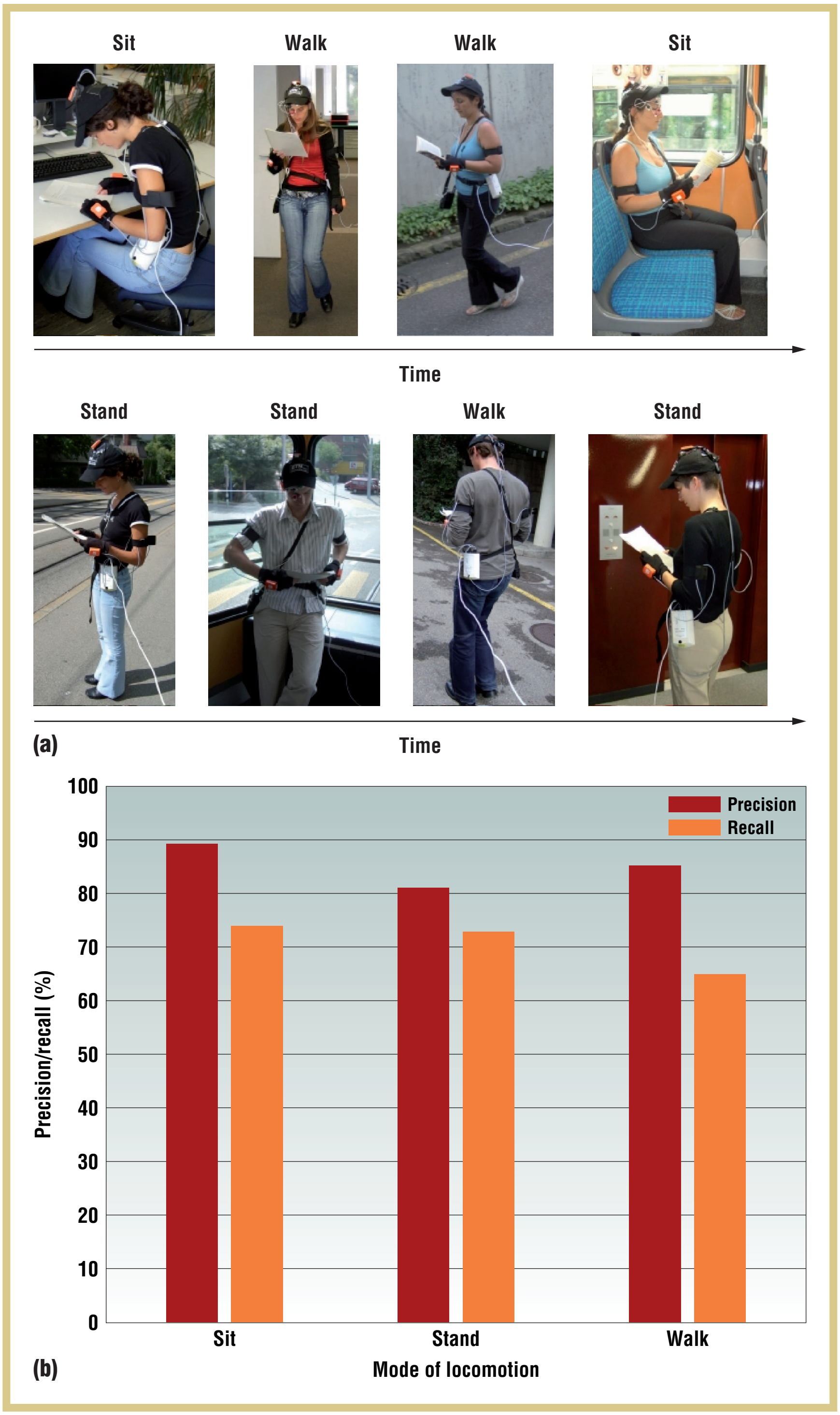

Figure 2. Measuring reading recognition. (a) Study participants reading during different modes of locomotion; (b) precision and recall for recognizing reading while sitting, standing, and walking.

distractions, we used Nintendo's wireless controller Wii remote for labeling. In total, we recorded an EOG dataset of roughly six hours with reading occurring about half of the time. This required spotting reading in a dataset of which approximately 50 percent were other types of eye movements (the so-called *null* class).

Reading has a regular pattern characterized by frequent, short scan saccades and less frequent, longer newline movements. We therefore chose to analyze the eyes' left and right saccadic movements. We recognized reading whenever a sequence of left and right saccades occurred in proportions close to those measured during training. Using person-independent training, we achieved an accuracy of 80.2 percent over all participants. Figure 2b shows the resulting precision and recall values for each of the three modes of locomotion.

This study's main finding was that EOG is a feasible measurement technique for recognizing reading in daily life scenarios. The results also showed that EOG is robust for different participants across a set of typical modes of locomotion. EOG's main advantage was that participants could wear relatively lightweight equipment. This helped the participants not feel constrained and allowed for natural reading behavior. One drawback was that we had to apply EOG electrodes to participants' faces, which participants might have regarded as inconvenient. In a postexperiment questionnaire, however, the participants reported that they did not feel constrained by either the electrodes or the connecting wires.

In a more recent work, we show that the performance for spotting and recognizing reading can be even further improved by incorporating information derived from other modalities, such as a person's head movements while looking down at the page.[9]

Case Study 2: Recognizing Office Activities

Our second study investigated the recognition of a set of typical office activities from eye movements recorded using EOG.[10,11] Eight participants took part in the study, which involved two continuous activity sequences, each lasting about 30 minutes. This resulted in a total dataset of about eight hours. Each sequence consisted of five activities performed in random order: copying a text between two screens, reading a printed paper, taking handwritten notes, watching a video, and browsing the Web. We also included a period of rest that represented the *null* class. For this period, we requested no activity from the participants but asked them not to engage in any of the previous activities.

We chose these activities for two reasons. First, they are all commonly performed during a typical working day. Second, they exhibit interesting eye movement patterns that are both structurally diverse and have varying levels of complexity. We believe that by their nature—some highly structured (such as reading), others less structured (such as watching a video)—these activities are a representative subset of the broad range of activities observable in daily life.

We conducted the experiment in a well-lit office during regular working hours. Participants were seated in front of two 17-inch flat screens, each with a resolution of 1,280 × 1,024 pixels on which a browser, a video player, and a word processor and text for copying were on-screen and ready for use. Sheets of paper and a pen were available on a desk near the participants. Participants could freely move their heads and upper bodies throughout the experiment.

For classification, we used a support vector machine (SVM) classifier. We developed 90 features based on three of the main eye movement types: saccades, fixations, and blinks. In addition, we devised features that capture information on repetitive eye movement patterns (see the "Eye Movement Characteristics and Features" sidebar). Figure 3a shows an example activity sequence, the corresponding horizontal and vertical EOG signals, four example eye movement features, and the final classifier output. As the figure shows, these features reflect characteristic differences in the eye movements performed during some of the activities. Copying (a combination of reading and jumping between screens) can be characterized by a high saccade amplitude variance (F22), and a high maximum horizontal saccade amplitude (F56). Reading involves many small horizontal saccades (F47) and a low mean fixation duration (F66). In contrast, watching a video and browsing are less well-structured activities and can hardly be distinguished only using the features shown here.

Using person-independent training, we achieved an average precision of 76.1 percent and recall of 70.5 percent over all classes and participants. Reading was a pervasive activity in this study as well—from quick checks of what had been written or copied, to reading longer text on a website or subtitles in the video. Consequently, there was some confusion between reading and browsing, which involves various subactivities that include reading (see the squares outlined in black in Figure 3b).

This study provided useful insights for the general problem of activity recognition using eye movement analysis. First, eye movements can serve as an alternative sensing modality for recognizing human activity without information on gaze direction. Second, good recognition performance required to use a combination of eye movement features. Information on repetitive patterns of eye movements proved useful, and can probably be extended to capture additional statistical properties. Because different recognition tasks likely require different feature combinations, we recommend considering a mixture of feature types for each new task.

Extending Context with a Cognitive Dimension

The findings from both studies underline the significance of eye movement analysis for context-awareness. The developed feature set and recognition system is person-independent and not limited to the chosen settings, activities, or eye tracking equipment. We therefore believe that eye movement analysis could be successfully applied to other context recognition problems in different settings, and for a broader range of visual and physical activities. Eventually, analyzing the link between unconscious eye movements and cognition might even pave the way for a new genre of pervasive computing systems that can sense and adapt to a person's *cognitive context*.

Cognitive context includes all aspects related to mental information processing, such as engagement, memory, knowledge, and learning. We define a computing system as cognition-aware if it can sense and adapt to a person's cognitive context.

Consider the following application. A business reception is held in a room equipped with a cognition-aware ubiquitous memory assistant system. Attendees wear eye trackers that let the system analyze their eye movement patterns while they look at other people's faces. From these patterns, the system can assess the memory recall processes, and can detect whether attendees know and remember each other. It can then automatically collect contact information about new acquaintances or send mnemonics about people a particular person has met before but does not remember.

This example application goes beyond matching faces to a database of previously encountered persons. It can only be implemented by extending the current notion of context with a cognitive

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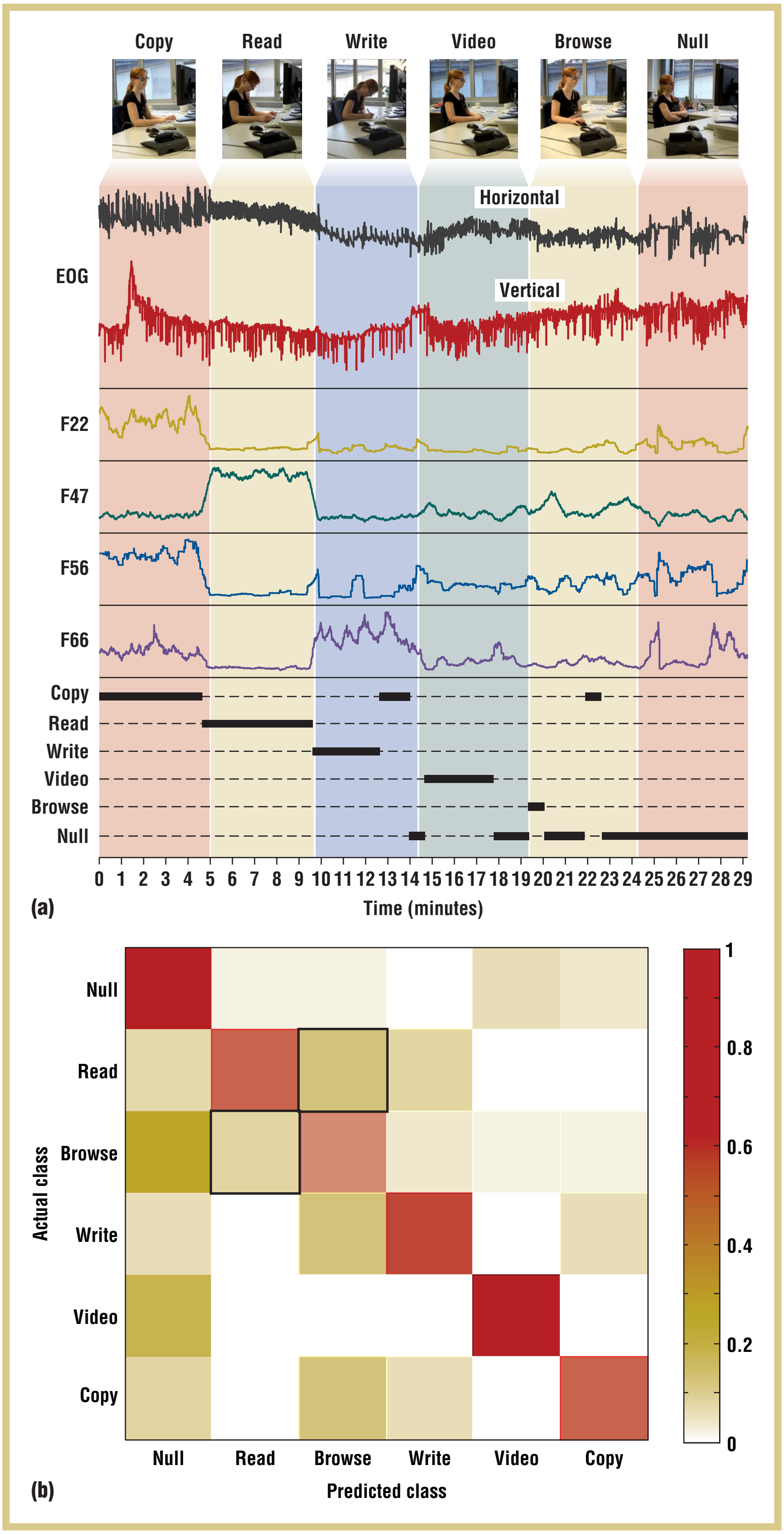

Figure 3. Recognizing and classifying office activities. (a) Example sequence of office activities, electrooculography (EOG) signals, example features, and classifier output; (b) color-coded classifier confusion for eye-based recognition of office activities (with an example confusion marked with black squares). This classification confirms specific eye movement characteristics in different activities.

dimension. Current context-aware systems, however, have a hard time assessing the cognitive context unobtrusively. The cognitive context is encoded in complex neural dynamics, and few obvious cues are accessible by noninvasive measurement techniques.

Cognitive Context from Eye Movements

A large body of research in cognitive psychology has found that unconscious eye movements are strongly linked to the underlying cognitive and perceptive processes. For example, researchers have shown that eye movements correlate with the type of memory access required to perform certain tasks, and are good measures of visual engagement[12] and drowsiness.[13] Differences in eye movement patterns were also found for people looking at familiar and unfamiliar faces,[14] and for doctors with different specialties when assessing tomography images. These findings show the rich information content available in eye movements related to cognition.

As a first step toward the example business reception application and our vision of cognition-awareness, we conducted an experiment to investigate the feasibility of assessing visual memory while looking at familiar and unfamiliar pictures. The experiment involved seven participants (three female and four male). The participants looked at four continuous sequences of pictures showing four categories of photographs: abstract images, buildings, faces, and landscapes (see Figure 4a).

We ensured that pictures in each category had similar visual features. For example, we selected landscape photographs showing a lake as their main feature, and faces and buildings were always centered. Within each sequence, we presented 12 pictures only once; we chose five others to present four times at regular intervals. We randomized this sequence across participants. The exposure time for each picture was 10 seconds. Between each exposure, we showed a picture with Gaussian noise for five seconds as a baseline measurement. The pictures were shown on a screen using a beamer resulting in a picture dimension of between 1 × 1 and 1.5 × 1.5 meters. Participants were seated 2 meters in front of the screen facing its center and were allowed to move their upper bodies at any time during the experiment. However, we encouraged them to sit still.

We recorded the participants' eye movements using EOG. We then extracted several features, including those known from the psychology literature to be linked to visual perception and memory recall. Figure 4b shows one of these features—the fixation count—for looking at faces with 0, 1, 2, and 3 prior exposures, averaged over all participants. As the figure shows, the mean fixation count decreased significantly with the number of previous exposures (significance level $p < 0.05$). This finding is akin to that of Jennifer Heisz and David Shore, who reported a similar correlation using a stationary video-based eye tracker.[14] The standard deviation across participants was larger in our study than in that work. We believe this is because of the limited dataset and might be improved by using more participants and longer sequences of pictures.

Nevertheless, the study revealed two important findings regarding the link between eye movements and (visual) memory recall processes. First, it is feasible to capture eye movement characteristics that reflect these processes using on-body sensors such as

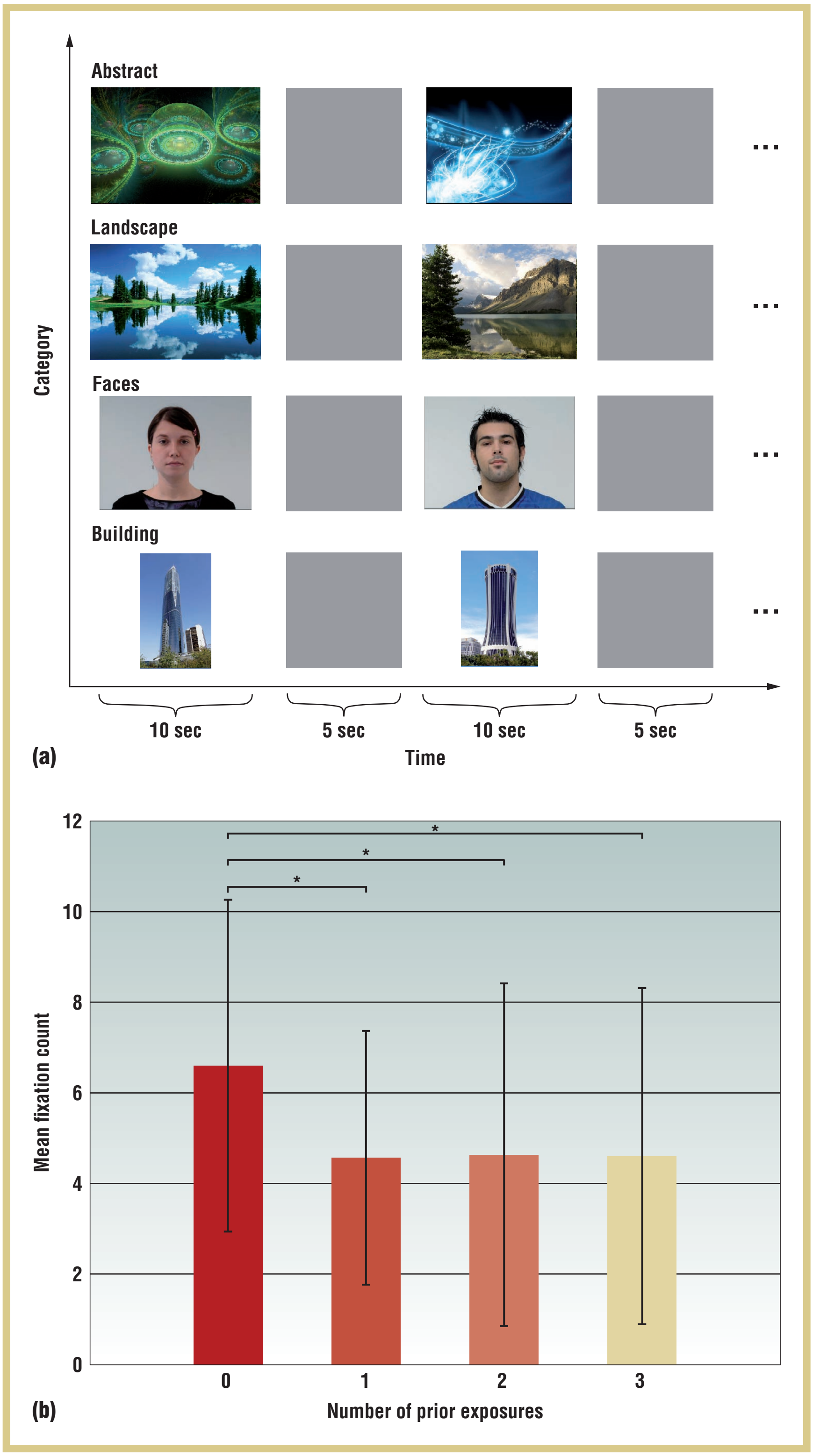

Figure 4. Visual memory experiment. (a) Example sequences with alternating pictures from four categories and Gaussian noise. (b) Mean fixation counts for faces with 0, 1, 2, and 3 previous exposures. The error bars represent the standard error of the mean across all seven participants. The asterisks indicate a significance level of $p < 0.05$.

EOG—that is, data acquisition and analysis is not limited to stationary video-based eye tracking systems. This finding is important in that it supports the use of wearable sensors for recording eye movements in mobile settings. Second, depending on the particular visual stimulus, only one eye movement feature—in this case the mean fixation count—might be enough to assess a person's memory recall. As a next step, we will analyze combinations of several eye movement features, and use our recognition system to automatically detect and quantify such memory recall processes.

Although these initial results are promising, developing cognition-aware systems for real-world applications faces several challenges.

First, assessing the cognitive context requires employing an appropriate experimental methodology. This methodology will be more similar to that used in experimental psychology than to that used in pervasive computing. In particular, specific cognitive processes must first be evoked reliably and measured in controlled settings before they can eventually be inferred in complex daily life situations.

Second, eye movement characteristics reflecting different cognitive processes must be identified, extracted from eye movement data, and automatically analyzed. This will likely require domain-specific modeling and machine learning approaches. In the simplest case, this means combining and adapting existing recognition methods for this new problem domain, as we showed. However, research on cognition-awareness will also require and drive the development of new methods geared toward cognitive context evaluation. This will probably require mechanisms that adapt to a person's specific eye movement characteristics.

Third, new questions in terms of engineering pervasive cognition-aware environments must be addressed. For example, interaction with artifacts that adapt to a person's cognitive context will open up new areas of research, particularly in HCI and design.

Finally, even if we only use eye movements to recognize activity, because we know that eye movements are influenced by cognitive processes, we must consider ethical and privacy issues. We must weigh the benefits of a cognition-aware system, such as the memory assistant outlined earlier, against the potential downsides. These issues are not unlike those raised by human activity recognition in pervasive computing environments. The wearable computing answer to these concerns might be to keep this information "on body" at first for a particular person.

Other challenges are associated with the co-influence of activity, situation, and cognitive processes on a person's eye movements. In the case studies presented here, either the activity or the cognitive process was predominant. Thus, we could consider each aspect separately. In real-world applications, however, eye movements are subject to a joint influence of activity, situation, and cognitive context. It is important to identify and separate these sources of influence for robust eye-based context recognition. We believe future research will therefore require a multidisciplinary approach at the crossroads of cognitive sciences, psychology, machine learning, and engineering.

Eventually, eye movement analysis, along with other measurement techniques such as portable electroencephalography (EEG) or functional near-infrared spectroscopy (fNIRs), might let us develop cognition-aware pervasive computing systems—a new genre of systems that can sense and adapt to a person's cognitive context.

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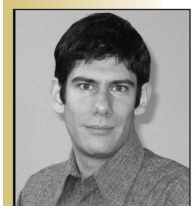

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