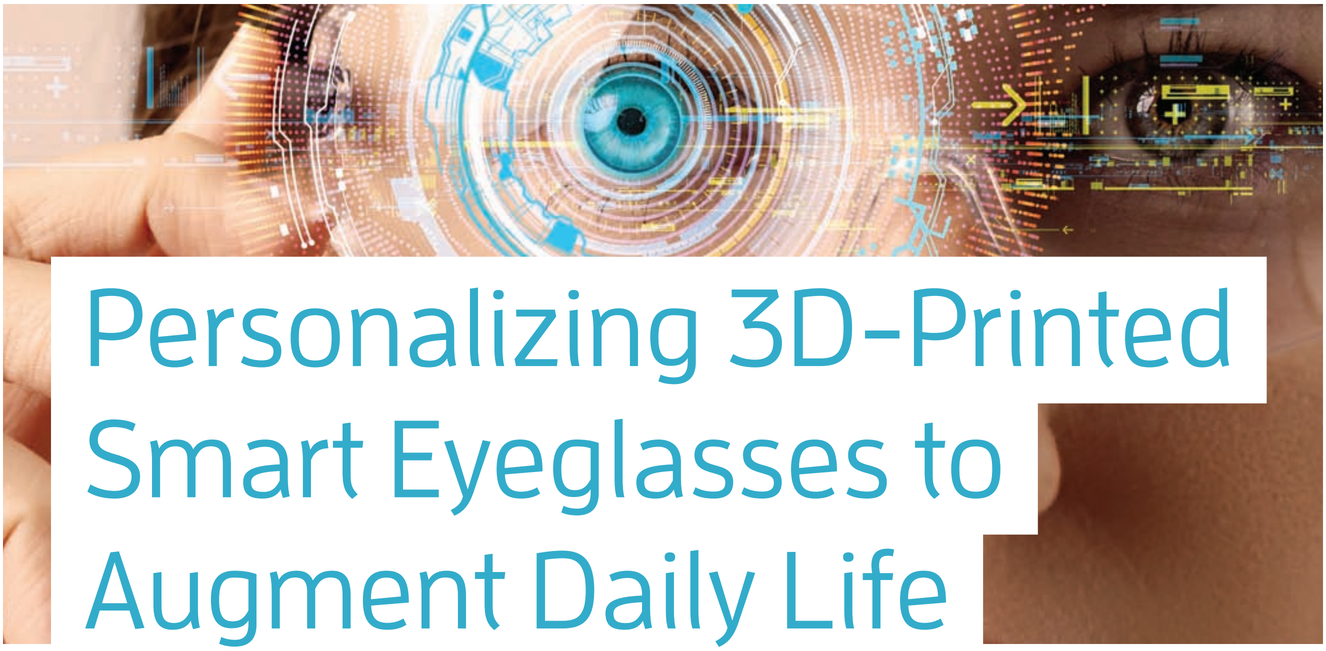

Personalizing 3D-Printed Smart Eyeglasses to Augment Daily Life

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Personalized 3D-printed eyeglasses equipped with sensing functions can enhance daily life through augmenting applications that enable wearers to monitor their vitals and behavior.

Eyeglasses are widely considered both a visual aid and a fashion accessory; with the addition of embedded technology, they'll be able to do much more to enhance wearers' daily lives. Because eyeglasses are positioned at a key site for continuous monitoring of physical, physiological, and environmental parameters, they could support a variety of health-monitoring applications. Future smart eyeglasses could track the daily activities of elderly users, alert computer users to extended screen use, and help dieters make better food choices, among other tasks (see the "Trends in Smart Eyeglasses" sidebar). Unlike smartphones, the adoption of smart eyeglasses will be driven by a rapid digital development process, and will require personalization to ensure comfort and usability.

With classic eyeglasses, opticians personalize the frames after they've been manufactured, usually by heating the plastic to tweak the frames to fit the wearer. This is not an option when electronics are involved, so smart eyeglasses should be personalized during the manufacturing process. Novel 3D-printing techniques and materials could provide the basis for personalized smart eyeglasses such that the frames are digitally printed and other functions are embedded using integrated electronics. After the lenses have been inserted, the eyeglasses can then be used to monitor the wearer's vitals and behavior using sensor data acquired from the head.

PERSONALIZED SMART EYEGLASSES

To begin personalizing smart eyeglasses, we analyzed head and face characteristics that influence the shape of eyeglasses and derived a set of free frame parameters (this refers to the degrees of freedom of the head model, as these parameters are adjustable and can be freely chosen). We modified a common frame design to embed sensors and processing electronics in the frames and temple tips. The frame parameters were subsequently fitted to different head configurations.

Head modeling

Because head and face shapes vary widely, we used open source human modeling software (MakeHuman; www.makehuman.org) to identify key head characteristics affecting frame design. Out of 146 available parameters to define head and face shape, we chose 26 that affect frame fitting. We reduced this to three parameters by removing those with a redundant effect on frame fitting.

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TRENDS IN SMART EYEGLASSES

The variety of uses for smart eyeglasses confirms that they could become a central monitoring component in human augmentation. However, acquiring reliable sensor data requires an accurate fit, so personalization is essential. Here we provide an overview of previous research, including our own, on smart eyeglasses.

Considering the head as a monitoring location, Oliver Amft and his colleagues presented an overview on the technical and application opportunities for smart eyeglasses.[1] Shoya Ishimaru and his colleagues used J!NS MEME, an electrooculography prototype, to perform activity recognition based on eye movement.[2] Florian Wahl and his colleagues built a smart eyeglasses prototype onto regular frames and evaluated inertial and other sensors for recognizing activity types.[3] Rui Zhang and his colleagues looked into smart eyeglasses performing dietary monitoring using electromyography electrodes.[4] Other researchers demonstrated further applications of head-worn wearable devices such as Google Glass. Shah Atiqur Rahman and his colleges used Google Glass to detect eating episodes in daily life,[5] and Javier Hernandez and his colleagues used the Google Glass gyroscope to measure heart rate while wearers remained still.[6]

Unobtrusive design will determine the successful adoption of smart eyeglasses. For example, Marion Koelle and her colleagues found that bystanders felt less comfortable around people wearing head-mounted displays because the wearers' intent was unclear.[7] In addition, Google Glass's integrated camera initiated many privacy discussions and slowed the device's adoption rates. Smart eyeglasses require careful choices in design, sensors, and interaction to remain unobtrusive and truly wearable.

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Alternative approaches to head modeling, such as light-based shape scanners, could be used, but measurements would be affected by occlusion due to ears and hair.

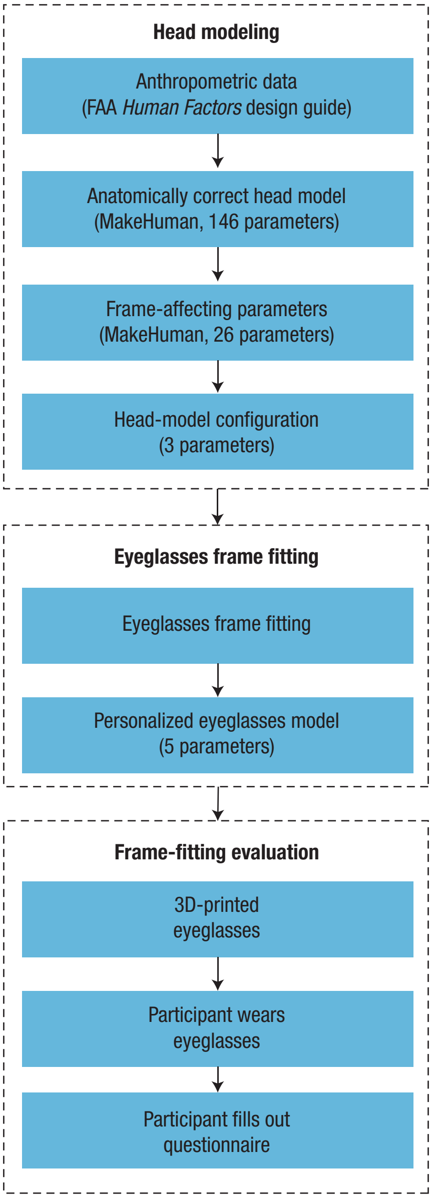
Parametric frame model

We used CAD software to develop a 3D frame model that closely resembles regular eyeglasses. Our aim was to create a parametric frame model with a minimal set of measurements that could be taken from the head. Initially, we mapped the 26 head- and face-shape parameters we identified to six free frame parameters controlling the frame model. We further refined this to five parameters and omitted nose-pad symmetry due to its low practical relevance.

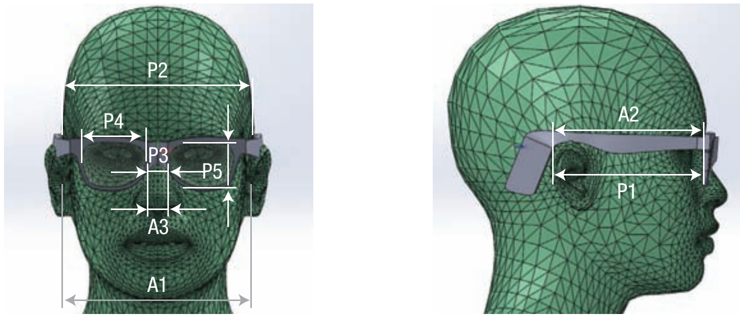
Figure 1 details the steps and parameters of our digital development process. Figure 1c shows the head- and face-shape parameters and the final frame parameters used. The frame temples were modeled by parameters for length, angle, and bend to ensure appropriate fit. The bridge has parameters for adjusting to nose width and height, lens height, and lens width. Accurate lens height is critical to prevent the frames from resting on the wearer's cheekbone.

Frame-fitting simulation

To verify that the five frame parameters would fit a range of head shapes, we used anthropometric head- and



(a)



(b)

	Head and face anthropometrics			Smart eyeglasses model parameters				
	A1 Head width (cm)	A2 Nose-ear distance (cm)	A3 Nose width (cm)	P1 Temple length (cm)	P2 Temple ends width (cm)	P3 Nose width (cm)	P4 Lens width (cm)	P5 Lens height (cm)
Model 1	12.5	18.8	1.3	8.7	11.5	1.5	4.3	3.5
Model 2	12.5	10.3	1.6	10.1	12.1	1.6	3.8	3.0
Model 3	12.5	11.5	1.9	11.5	12.2	1.9	3.8	3.0
Model 4	14.2	9.2	1.5	9.1	13.4	1.5	5.0	3.8
Model 5	14.2	10.2	1.9	10.6	13.4	1.6	4.7	3.3
Model 6	14.2	11.2	2.1	11.7	14.1	1.9	4.6	3.0
Model 7	15.9	9.2	1.7	9.1	15.1	1.6	5.4	3.4
Model 8	15.9	10.6	2.1	10.5	15.3	1.8	5.2	3.2
Model 9	15.9	11.8	2.4	11.8	15.7	1.8	5.1	3.0
Participant 1	15.0	11.0	1.4	10.9	14.3	1.4	5.9	3.1
Participant 2	13.1	10.6	1.8	10.5	10.8	1.8	5.3	3.8
Participant 3	14.5	11.0	1.1	10.9	13.5	1.4	5.2	3.3
Participant 4	14.1	11.1	1.6	11.0	12.2	1.6	4.2	3.0

(c)

(d)

FIGURE 1. Smart eyeglasses development process steps, head configurations, and frame parameters. (a) Digital development process to personalize smart eyeglasses. (b) Example head-model configuration according to data from the Federal Aviation Administration's (FAA's) *Human Factors Design Standard* guide and fitted frames. Anthropometric and free frame parameters are indicated. (c) Parameters of head model configurations, participants, and fitted CAD frame model parameters. (d) Study participant wearing fitted 3D-printed eyeglasses.

face-shape data from the US Federal Aviation Administration's *Human Factors Design Standard* guide.[1] With this data, we derived measurements to generate nine head-model configurations using MakeHuman. We selected the head length and width to match humans in the 1st, 50th, and 99th percentiles.

After importing a generated head model into the CAD software, we took a series of head measurements to match the frames to the head. Figure 1b shows an example head-model configuration with the fitted frames and measurements for the head model.

Hardware

The major difference between our smart eyeglasses and regular frames is that we inserted pockets into the temple tips that house the battery and main processing unit (including a microcontroller unit, flash memory, and a wireless unit). These components are distributed onto both temple tips to balance the weight, and wiring inside the frames connects the different components. To emphasize unobtrusive design, the frames do not include interaction functions such as touchpads or buttons. They will pair with smartphones to support interaction and offload processing.

Physical frame-fitting evaluation

In addition to the simulations, we fitted the frames to four users (two female and two male) using the same personalization procedure. Participants were asked to wear the frames for one day and rate their comfort. All participants wore eyeglasses regularly and switched to contact lenses for the study duration. After receiving detailed information about the evaluation process, participants gave written consent for the use of their data and images.

We measured each participant's temple length, ear-to-nose distance, and nose width, and adjusted the CAD frame parameters to personalize each pair. We printed the personalized eyeglasses on a 3D printer (Witbox with Diamond Hotend) but did not integrate lenses or electronic components as the focus of this study was to evaluate frame personalization. Due to the printing process, frame weight was 28 g, similar to regular eyeglasses. Figure 1d shows a participant wearing our 3D-printed personalized eyeglasses.

After wearing the frames for a day, participants completed a questionnaire on fit and comfort, with six items rated on a five-point Likert scale. Participants completed the same questionnaire to rate their usual eyeglasses. We found that they considered the printed frames comfortable to wear overall (4.25 of 5) and slightly futuristic (3.5 of 5). Compared to participants' usual eyeglasses, the printed eyeglasses were found to be similar in comfort. All study data can be found in the electronic appendix at www.actlab.uni-passau.de/~fwahl/IEEE_Computer_Wahl_2017/appendix.pdf.

SMART EYEGLASSES COULD REPLACE REGULAR EYEGLASSES AND ACTIVITY TRACKERS FOR MANY WEARERS.

APPLICATIONS FOR SMART EYEGLASSES

Here we describe three important applications of smart eyeglasses, though there are many other potential functions.

General health and fitness tracking

Wearable devices that track daily activity such as steps and heart rate (for example, Fitbit) have become popular, but suffer from low long-term compliance.[2] Smart eyeglasses could replace regular eyeglasses *and* activity trackers for many wearers.

Inertial sensors, including accelerometers and gyroscopes, can recognize various activities of daily living (ADLs). Inertial sensors measure head motion and posture that reflect different repetitive movements such as walking, running, and cycling, as well as static activities such as reading. They do not depend on a particular head position and, thus, can be placed anywhere in the frames. Moreover, heart activity can be monitored using a pulse oximeter (PPG) sensor at the temples. While monitoring physical and cardiac activity, the glasses could provide daily or weekly feedback on aggregated behavior patterns and trends through a wirelessly connected smartphone or website.

In our earlier work, we investigated using smart eyeglasses to recognize ADLs within nine activity clusters, such as walking, eating, and reading.[3] We recorded data from nine participants, who either did not require prescription glasses or wore contact lenses during recordings. An observer labeled the recordings using a smartphone[4] while participants followed a scripted protocol to maximize the ADLs. From a total of 66 hours of data, we derived 25 time-domain features of acceleration and gyroscope axes using a 30-s sliding window with 1-s step size. We applied principal component analysis (PCA) to reduce time-domain features (for example, acceleration mean, variance, minimum, and maximum) from 175 to 78, such that the retained features still explain 99.9 percent of the variance. We used Gaussian mixture models (GMMs) to classify activity clusters using leave-one-participant-out (LOPO) cross-validation. This ensured that the classifier was tested independently of its training data. Using a GMM with three Gaussian components and diagonal covariance matrix, all activity clusters except cycling were detected with an accuracy of at least 80 percent. Using a class-reject design, overall classifier accuracy was 77 percent on average, varying from 70 to 84 percent per participant. See Figure 2 for an overview of the ADL experiments.

SMART EYEGLASSES COULD CONTINUALLY PROVIDE RELEVANT FOOD-CONSUMPTION DETAILS FROM DIFFERENT INTEGRATED SENSORS.

Circadian rhythm and screen-use detection

The human body's internal clock (circadian rhythm) is controlled by the intensity and timing of light received through the eyes. Detecting light in the morning advances the circadian phase, while detecting light in the evening delays it. Phase shifts of –2 to +3 hours per day are possible.[5,6] Misalignment of circadian rhythm and external time can lead to impaired performance, alertness, and gastrointestinal functions. Circadian misalignment and regular sleep deprivation are a known issue for a large part of the population. In addition, the relatively high energy in the blue light emitted by LED screens (found in computers and smartphones) affects the circadian phase by inhibiting the sleep-stimulating hormone melatonin.[7] Extended screen use in the evening and at night can lead to circadian phase delays and reduced sleep quality.

Our smart eyeglasses feature a color-light sensor (ams; ams.com) that measures light exposure throughout the day. The sensor is built into the bridge to align it closely with the eyes' viewing direction. Light exposure profiles and detection of screen use could help estimate circadian phase shifts and provide general behavioral recommendations. For example, real-time information about accumulated light exposure combined with blue light detection could be used to recommend blue light software filters, or automatically enable such filters for the computer or smartphone screen.

To analyze screen use and light detection, we performed a study with 14 participants (2 female and 12 male). Each participant was asked to read a print article and browse the Internet on a HP EliteDisplay E241i 24-inch screen at 70 cm distance for 20 minutes per activity. Participants wore the smart eyeglasses to record red, green, blue, and clear color channels with a sampling rate of 6.5 Hz (see Figure 3). Ambient light intensity was recorded at the beginning of each recording session using a standard lux meter (Amprobe; www.amprobe.com). From a total of 15.2 hours of data, we identified 18 time-domain features comprising light-channel ratios using a sliding window of 5 s and 50 percent window overlap. With a linear support vector machine, screen-use episodes were detected using LOPO cross-validation. The ratios of the light intensities between color channels clearly distinguish screen use from other activities. Detection accuracies for screen use averaged 90 percent. When the ambient light intensity was 500 lux or less, as in a typical evening scenario, average accuracy peaked at 95 percent. For ambient light intensity above 500 lux, which is the recommended indoor light intensity in office spaces,[8] screen-use detection accuracy still reached 85 percent.

Nutrition monitoring

Dietary coaching and nutrition monitoring based on actual intake patterns can help people with cardiovascular disease, diabetes, or obesity and those concerned about their personal health. Conventional nutrition monitoring requires users to manually log their dietary routines. However, this type of logging is known to result in low adherence of recording every intake

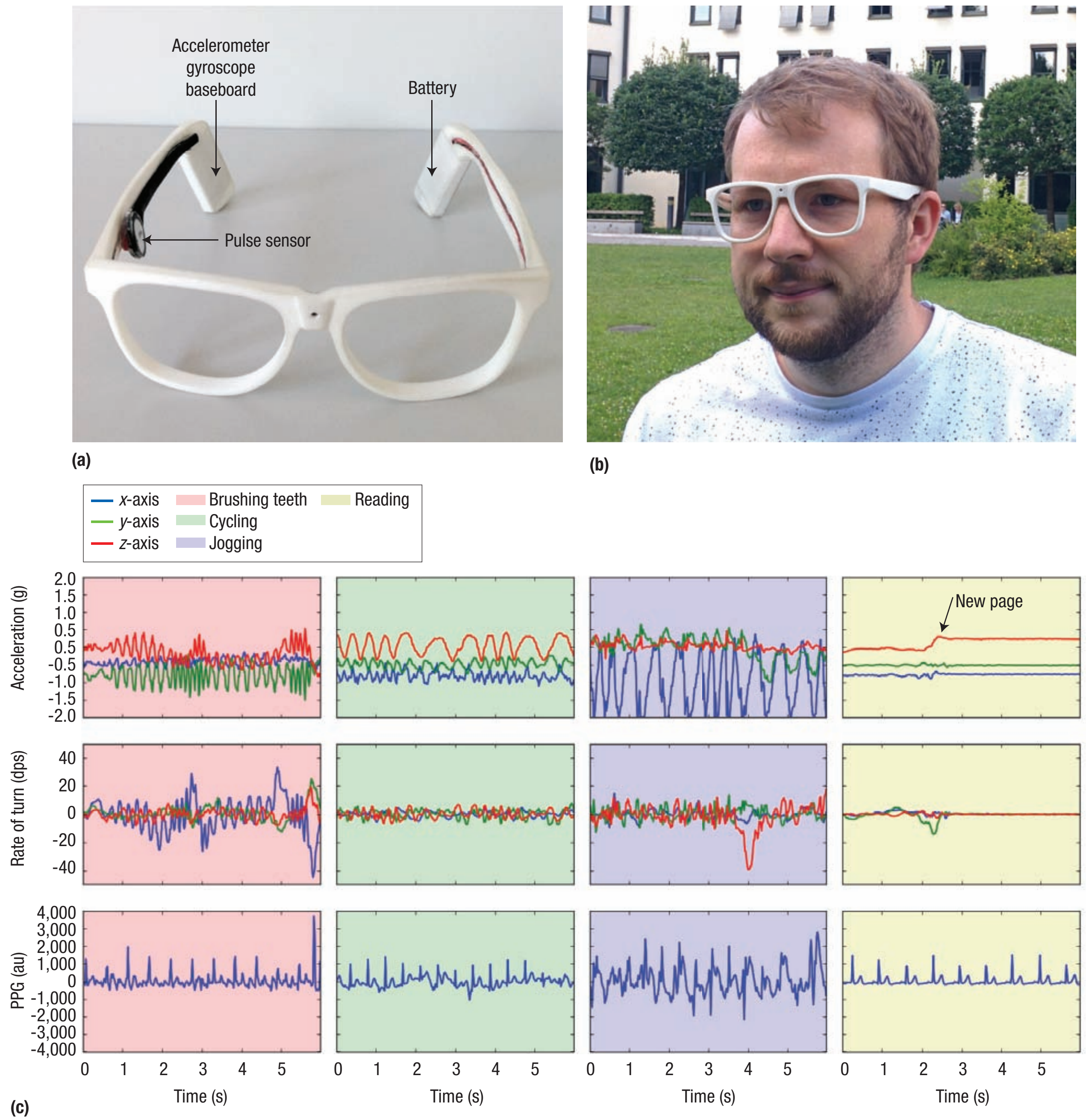


FIGURE 2. Activity recognition results. (a) Frame prototype with inertial sensors (InvenSense; www.invensense.com) at the temple tips and a pulse oximeter (PPG) used to detect activities of daily living (ADLs). (b) Participant wearing smart eyeglasses during ADLs. (c) Example accelerometer, gyroscope, and PPG sensor data during typical ADLs. The data shows, for example, head movement when beginning to read a new page, as well as repetitive patterns of different frequencies during activates like brushing teeth, jogging, and cycling. dps: degrees per second; au: arbitrary units.

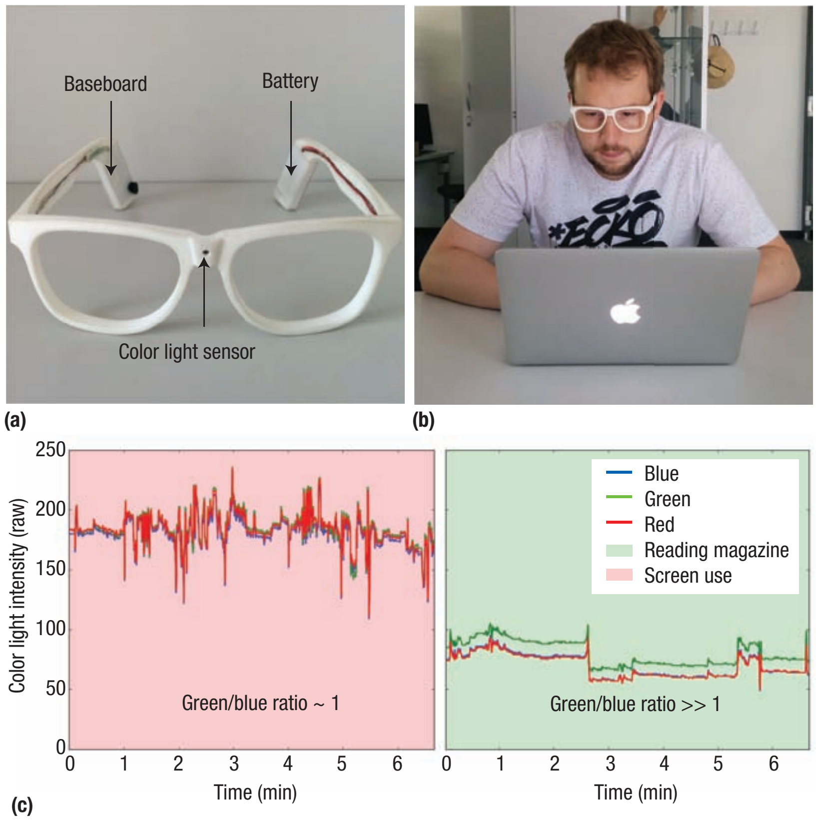


FIGURE 3. Screen-use detection with smart eyeglasses. (a) Smart eyeglass components for screen-use detection. (b) Participant wearing smart eyeglasses while performing activities. (c) Example light intensity data for red, green, and blue color channels while using a screen and reading a print magazine. Ratios of color channels clearly differ between activities.

detail, rendering self-reporting highly inaccurate. Aside from forgetting to log details, users can choose to omit entries, such as a high-calorie evening snack. Smart eyeglasses could solve this challenge by continuously providing relevant food-consumption details from different sensors integrated into the eyeglasses.

Although facial surface electromyography (EMG) has been shown to effectively monitor chewing, it has been disregarded for wearable nutrition monitoring because of the prominent placement of electrodes on the head. However, eyeglasses offer a way to integrate EMG-based chewing monitoring in a wearable accessory, as the frames make contact with the skin at several key areas.[9] The bilateral temporalis muscles are of primary interest for monitoring chewing, as they span a large area of the skull from the temples to the ears and are used to elevate the jawbone for each chewing cycle. Most of the muscle area is covered by hair, which is inconvenient for surface EMG measurements. Nevertheless, there are small spots around the ears that offer sufficient EMG signal quality.

Another relevant information source is the skull vibration generated during chewing. Breaking food pieces into particles generates mechanical vibrations that spread from the teeth throughout the skull.[10] The vibrations can be detected at the mastoid bone and other skull regions, such as behind the ears. For nutrition monitoring, personalizing smart eyeglasses is key to match EMG and vibration sensors to recording landmarks and to maintain skin contact. Recorded data is processed via the eyeglasses and can either instantly interact with the wearer (for example, to ask for confirmation of the detected food consumption), or provide daily or weekly feedback on dietary patterns via a connected smartphone or website.

We investigated different areas along the smart frames to find the optimal EMG electrode locations.[9] The temporalis muscle regions just above the ear showed consistently high signal-to-noise ratios for differential EMG measurements. We embedded textile electrodes in the temple tips and a reference electrode in the nose pad. While EMG data provides a segmentation of chewing cycles, vibration measurements serve to discriminate different food categories from their material textures.

Figure 4 shows the smart eyeglasses prototype integration and example EMG and vibration signals during chewing and other activities. We conducted a study with eight participants (four female and four male, ranging from 20 to 56 years old) and recorded chewing of five different food types representing different textures: carrot, toast, jelly candy, banana, and crackers. To analyze a realistic condition for detecting chewing cycles, participants also performed other activities, including speaking, coughing, and moving the head. Chewing was performed on alternating jaw sides and at different speeds. We detected the chewing cycle with ~38.5 min of data per participant and a total of 5,435 chews. We employed the mean rectified and filtered EMG signal value within a sliding window of 200 ms, $\bar{x}$, and compared it to a threshold, $\theta = \mu + n \times \sigma$, where n is an adjustable scalar and (μ, σ) are a Gaussian model of the baseline noise. When $\bar{x} > \theta$, the window was regarded as part of a chewing cycle, and a series of continuous windows was regarded as a chewing-cycle candidate. By majority voting on the windows and retaining chewing-cycle candidates within typically ~400 ms to 1 s, we determined the final detected chewing cycles. Although the detection could certainly be refined, we obtained 80 percent precision and recall, confirming that the EMG activation pattern during chewing is a robust chewing-cycle indicator.

Although we built separate frame prototypes for each of the applications described, they could be integrated into one pair of frames. However, some applications might require dedicated eyeglasses due to sensor placement. Moreover, the frame design influences how functional components can be embedded and how frame model parameters might be chosen. We expect that for further applications and frame designs, the digital development process could be repeated.

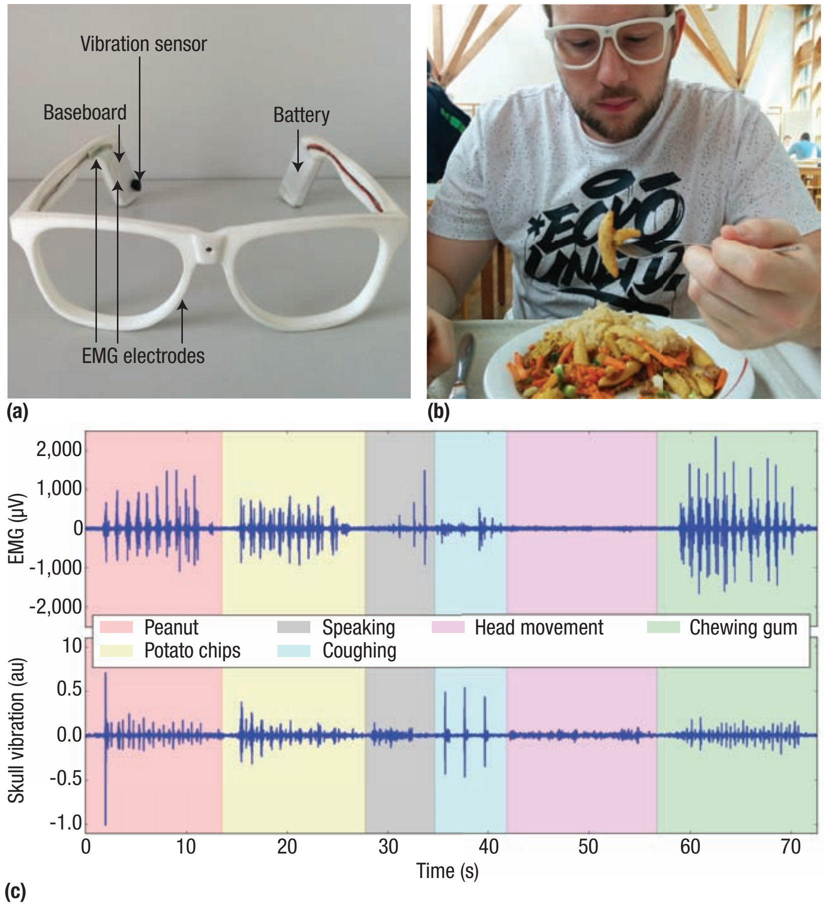


FIGURE 4. Nutrition monitoring with smart eyeglasses. (a) Smart eyeglasses components used to monitor chewing. (b) Participant wearing smart eyeglasses in daily life. (c) Example surface electromyography (EMG) and skull vibration data during a series of chewing and non-chewing activities. Signal patterns differ among activities.

Personalized wearable accessories could address a multitude of open challenges in wearable computing. First, personalized items might be used more frequently than common items as they are designed and manufactured according to individual preferences. Second, accessories that are fitted to individual anatomical requirements will be more comfortable for the wearer. Third, rather than just providing a single sample that could be affected by random noise, wearables can analyze multiday trends in sensor data to help users understand behavior change.

With proper personalization and fashionable design, smart eyeglasses might replace their classic counterparts. Among the current top 20 eyeglass designs,[11] 18 models would support integrated electronics and our personalization approach. In the US, 64 percent of the population wears eyeglasses.[12] Even beyond regular wearers, sunglasses, sports glasses, and safety glasses could feature sensors for human augmentation.

Digital printing offers abundant options for frame shape and color and

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enables developers to quickly address niche applications, but integrating electronic and printed components in mass production remains an open challenge. As printing techniques and materials evolve, additional functionality could be printed directly, including sensors, wiring, and basic electric components—but integrated electronics are unlikely to be fully replaced. As electronic components, including sensors and processing units, can be embedded across different wearable accessories, they remain volume-produced and thus available at low cost. We believe that hybrid systems of electronic and printed components will spawn an entirely new generation of wearable systems.

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