



Soft, conformal bioelectronics for a wireless human-wheelchair interface

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ABSTRACT

There are more than 3 million people in the world whose mobility relies on wheelchairs. Recent advancement on engineering technology enables more intuitive, easy-to-use rehabilitation systems. A human-machine interface that uses non-invasive, electrophysiological signals can allow a systematic interaction between human and devices; for example, eye movement-based wheelchair control. However, the existing machine-interface platforms are obtrusive, uncomfortable, and often cause skin irritations as they require a metal electrode affixed to the skin with a gel and acrylic pad. Here, we introduce a bioelectronic system that makes dry, conformal contact to the skin. The mechanically comfortable sensor records high-fidelity electrooculograms, comparable to the conventional gel electrode. Quantitative signal analysis and infrared thermographs show the advantages of the soft biosensor for an ergonomic human-machine interface. A classification algorithm with an optimized set of features shows the accuracy of 94% with five eye movements. A Bluetooth-enabled system incorporating the soft bioelectronics demonstrates a precise, hands-free control of a robotic wheelchair via electrooculograms.

1. Introduction

A recent study shows that more than 10% of US population has some type of motor disability (Brault, 2012); 3.6 million people rely on wheelchairs and 6.7 million people have difficulty grasping low weight objects. For those with frail grip strength, an alternative wheelchair interface is needed, which can be helped by human-machine interfaces (HMI). Multiple studies have demonstrated HMI applications (Aziz et al., 2014; Barea et al., 2002a; Belkacem et al., 2015; Keegan et al., 2009; Wu et al., 2013) and activity tracking (Bulling et al., 2009; Mala and Latha, 2014) via non-invasive electrooculograms (EOG). EOG signals are derived from the potential that is created by the eye acting as a dipole through the positively charged cornea and negatively charged retina. Typical amplitudes of signals range from 50 μ V to 3500 μ V and are caused by the amount light incident on the retina (Barea et al., 2002a, 2002b).

The most important factor for successful HMI is to have high accuracy in signal classifications that are utilized for a machine control. Algorithms to enable multi-class differentiation use various features for

maximized accuracy of subject-dependent signals. The continuous wavelet transform, Haar wavelet, is one of the most widely used features for EOG recognition (Aziz et al., 2014; Belkacem et al., 2015; Bulling et al., 2009; Mala and Latha, 2014). For example, this feature was included in a classification method (Bulling et al., 2011) for multiple task recognitions such as copy, read, write, video, browse, and null.

A recent use of EOG (Belkacem et al., 2015) shows 90% accuracy of eye movements using both EOG and electroencephalograms for computer interfacing and 80% accuracy for manipulation of a robotic arm (Hortal et al., 2015). Nevertheless, the critical issue comes from the use of gels and sticky tapes, which cause skin irritation and allergic reactions. To address the issues, our prior works introduced a “skin-like” electronic system, which offered a non-invasive, high quality recording of biopotentials on the skin (Jeong et al., 2013, 2014; Lee and Yeo, 2015; Xu et al., 2016; Yeo et al., 2013a, 2013b).

In this work, we focus on soft bioelectronics and wireless wheelchair interface (Fig. 1). This ergonomic HMI system incorporates conformal biosensors and a Bluetooth unit interfacing the bioelectrode

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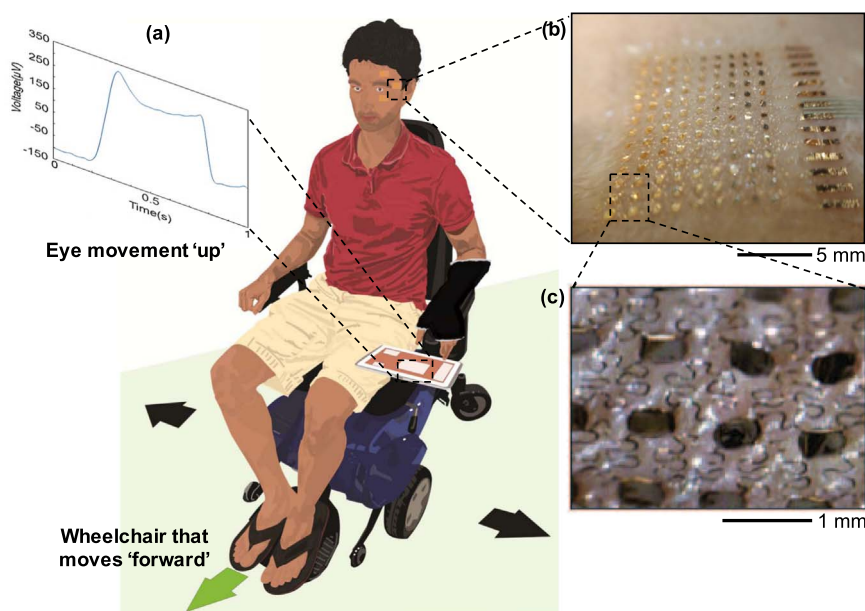


Fig. 1. Soft bioelectronics for a tether-free wheelchair control via electrooculograms (EOG). (a) Illustration of a subject wearing skin-mounted, fractal electrodes to control the robotic wheelchair via EOG signals (inset graph) and a tablet-operated wireless interface. (b) Photo of the exploded view of the soft electrode mounted around the eye. (c) The magnified view of (b) representing a conformal contact of the electrode on the skin.

with a robotic wheelchair. The “skin-like” bioelectrode enables a high-fidelity recording of EOG, supported by the direct comparison with conventional rigid electrodes. This soft bioelectronic system demonstrates mechanical compliance in both stretchability (30%) and bendability (up to 180°). A newly designed classification algorithm with an optimized set of features shows the accuracy of 94% with five different eye movements, which is used to demonstrate a hands-free control of a robotic wheelchair via EOG.

2. Materials and methods

2.1. Finite element analysis

Three-dimensional finite element analysis using a software (ABAQUS, Dassault Systems, Waltham, MA) was conducted to investigate mechanical behaviors of an electrode upon skin deformations: bending and stretching (Chen et al., 2016; Ma et al., 2016). The soft electrode used in EOG measurement was composed of three layers including 300 nm-thick Au, 1 μm -thick polyimide (PI; HD Microsystems, Parlin, NJ), and 5 μm -thick silicone elastomer (Smooth-On, Macungie, PA; details in Supplementary Fig. S1). Young's modulus (E) and Poisson ratio (ν) of materials used in the modeling are $E_{\text{silicone}} = 69 \text{ kPa}$ (Yeo et al., 2013b) and $\nu_{\text{silicone}} = 0.49$ (Zhang et al., 2014) for a silicone elastomer; $E_{\text{Au}} = 78 \text{ GPa}$ and $\nu_{\text{Au}} = 0.44$ for Au (Zhang et al., 2014); $E_{\text{PI}} = 2.5 \text{ GPa}$ and $\nu_{\text{PI}} = 0.34$ for polyimide (Zhang et al., 2014). The maximum principal strain on Au was mainly investigated to determine the mechanical stability upon multi-modal deformations. Note that Au membrane was used as an electrode, PI was a supporting layer to hold the membrane, and silicone elastomer was a substrate to mount the electrode.

2.2. Fabrication of a soft bioelectrode

Fabrication of a soft electrode was based on the combination of a conventional photolithography (details in Supplementary Fig. S2) with material transfer printing (details in Supplementary Note 1 and Supplementary Fig. S3). A glass slide (Ted Pella, Redding, CA) was prepared by a cleaning process using acetone, IPA, and rinse with DI water. Afterwards, a primer (MicroChem Corp., Westborough, MA) was coated on the substrate for enhanced adhesion. Multi-layer coating and

curing of PMMA and PI was followed. The electrode patterning started with Au deposition on the PI and photolithography defined patterns. A second layer of PI was encapsulated while exposing the skin contacted patterns and wire connection pads. The electrode was retrieved by a water soluble tape after dissolving the sacrificial PMMA in solvent. Afterwards, it was transfer printed on an ultrathin elastomeric membrane (5 μm in thickness) on a polyvinyl alcohol film. Lastly, a flexible film was attached onto contact pads for connection with a wireless system (BioRadio; Great Lakes NeuroTechnologies, Cleveland, OH).

2.3. Measurement of mechanical behavior

Biaxial stretching of the fabricated electrode was conducted on a programmable stretcher (details in Supplementary Fig. S4). The stretcher held a sample with four clamps. Precise control of the travel distance by an Arduino and stepper motors determined the applied strains. Ultrathin copper wires (100 μm in diameter) were connected to the electrode for recording of resistance change by a digital multi-meter (Model 2100, Keithley, Cleveland, OH). In a bending test, a sample was placed on a flexible plastic film, which allowed bending from 0 to 180° with the radius of curvature of 500 μm . Similar to the stretching test, electrical resistance was monitored according to the degree of bending. We utilized a portable microscope (Dino-Lite, Torrance, CA) to inspect any localized, microscale fracture.

2.4. In vivo measurement of EOG

Three healthy males, aged from 20 to 25, participated in EOG measurement based on the approved protocol (HM20001454) at Virginia Commonwealth University. All subjects with 20/20 vision were given an explanation for the study and signed a consent form. For EOG recording, two sets of electrodes were placed on the skin around the eyes. For horizontal eye movements, each electrode was positioned 1 cm away from the outer canthus of each eye. For vertical eye movement, left eye was selected; one was mounted 1 cm away from the eyebrow and the other was positioned 1 cm away from lower eyelid. A common ground was positioned on the forehead.

2.5. Data acquisition

Fractal bioelectrodes were configured to work with a commercial wireless unit. A two channel setup was configured with a sampling rate of 500 Hz. We made a quantitative signal comparison between commercial Ag/AgCl electrodes (MVAP II, Newbury Park, CA) and fractal electrodes. The measured EOG signals were wirelessly transmitted to a receiver connected to a laptop or tablet interface with a data acquisition interface.

2.6. Human-wheelchair interface

A subject was given auditory commands to start training by following the direction of the customized interface. A total of 40 trials were obtained for four classes (up, down, left, and right). Afterwards, each user tested the accuracy of trained data. Again, auditory commands were given to initiate the classification. Twenty commands for five classes were provided in the classification interface. Users repeated this process three times for conventional and fractal electrodes. The overall accuracy was acquired from the sum of all three trials.

3. Results

3.1. Design and characterization of a soft electrode

Skin-wearable, soft electrodes were designed to have mechanical stretchability for intimate contact to the dimpled skin and avoiding any failure caused by dynamic skin deformations. Finite element analysis (FEA) played a key role to design a highly deformable structure. We explored a self-similar, open-mesh structured ‘fractal’ patterns (Hattori et al., 2014). We used an array of circular disks, interconnected by the fractals, which offered an improved areal coverage for an enhanced signal-to-noise ratio. The FEA result in Fig. 2a and c captures the stretching behavior of the electrode upon tensile strains and bending; the fractal interconnects in the design absorb the applied stress to isolate it from the disks. The maximum principal strain, applied to Au, is less than 2% under the biaxial strain (30%) (Fig. 2a), which is well under the fracture strain (5%). A microscopic observation and quantitative mechanical test follows to validate the mechanics analysis (Fig. 2b and d). A microscopic investigation monitors visual defects

on the structure, caused by mechanical fracture during cyclic stretching (Fig. 2b) and bending (Fig. 2d). Two-point resistance measurement upon repetitive loading and unloading quantifies the structural safety since any abrupt spike in the plot captures unexpected fracture. A cyclic mechanical test includes an increment of 5% tensile strains and 10° folding for the stretching and bending test, respectively. In this mechanical study, we apply additional safety factors by considering a maximum strain upto 30% and bending upto 180° (with 500 μ m of radius of curvature), which still shows negligible resistance change on the electrode (Fig. 2e and f). Note that normal human external tissues stretch upto ~20% without tissue damage (Yeo et al., 2013b) and typical skin deformation does not exceed the selected bending curvature (Hattori et al., 2014). Overall, the FEA and experimental results ensure that the fractal structure makes a suitable electrode even if a user has unusually developed dimples and habits to create exaggerated facial expressions (Bao et al., 2007).

3.2. Measurement of EOG signals

A set of the fractal-structured electrodes was used to record target EOG signals on the skin (details in *Materials and Methods*). For a long-term, persistent HMI demonstration, we conducted electrophysiological measurement, without the use of any conductive gels and acrylic adhesives. The fractal electrode measured four kinds of EOG signals from different eye movements involving up, down, left, and right (Fig. 3). The same experimental procedure was applied for both conventional and fractal electrodes for side-to-side comparison (photo of both electrodes in *Supplementary Fig. S5a*). The EOG data recorded by skin mounted electrodes were wirelessly transmitted to a data acquisition unit for signal processing (photo of the setup in *Supplementary Fig. S5b*). Raw EOG signals in Fig. 3a, measured by vertically mounted electrodes, compare ‘up’ and ‘down’ movements. Both conventional and fractal settings show very similar signal amplitudes along with the baseline noise. Horizontal electrodes (Fig. 3b) capture higher EOG signals (600–750 μ V) than the vertical motions (~400 μ V) where the signal strength is dependent on the amount of angle change of the eyes. The direct signal comparison via derivative filtering (Fig. 3c and d) makes clearly distinguishable features of target signals. This filtering step decides the correct threshold for data processing in a classification algorithm. In the given

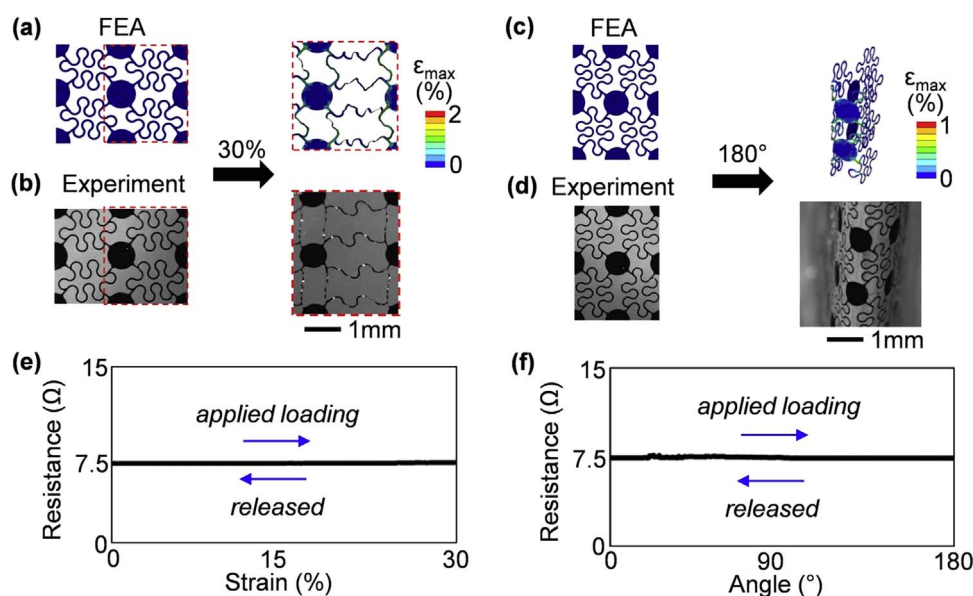


Fig. 2. Computational modeling and experimental validation of a fractal structured electrode upon mechanical deformation. (a, b, c, d) Comparison between the finite element analysis (FEA) results and experimental observations with (a, b) biaxial tensile strains upto 30% and (c, d) bending upto 180 degrees with the radius of curvature (R) of 500 μ m. (e, f) Quantification of electrical resistance according to the (e) applied strains and (f) bending; (e) cyclic mechanical test with repetition of loading and unloading and (f) cyclic mechanical bending test. The scale bars in the FEA data indicate the maximum principal strain applied on the electrode.

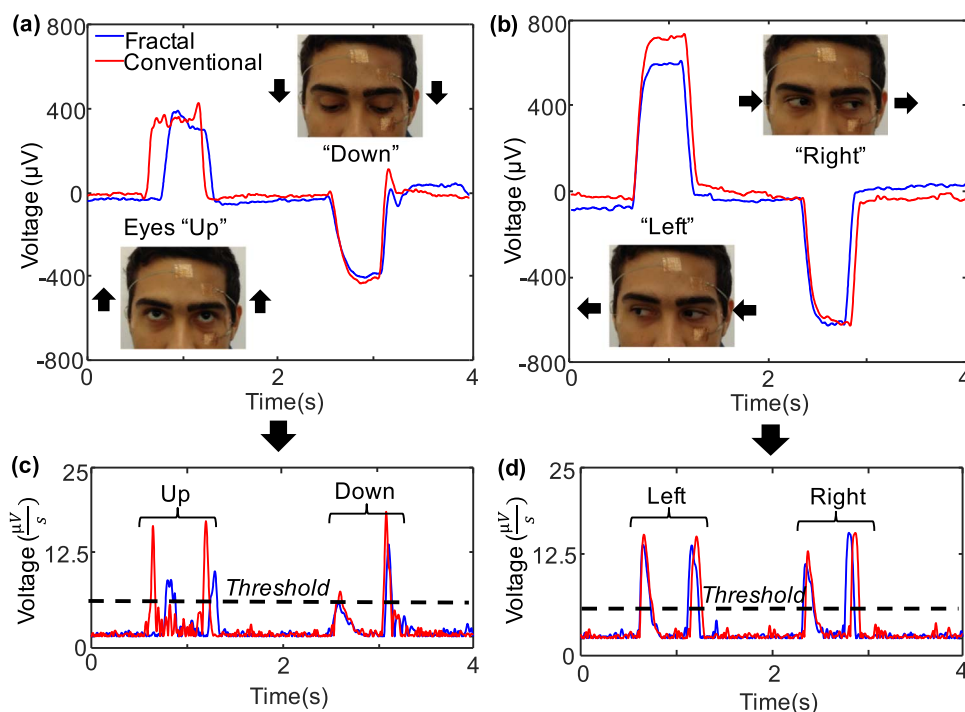


Fig. 3. A representative set of EOG signals involving four kinds of eye movements. (a–d) Direct comparison of raw EOG signals measured from fractal and conventional gel electrodes: signals from (a) eyes ‘up’ and ‘down’ motions and (b) ‘left’ and ‘right’ motions. Bandpass (0.1–20 Hz) filtered EOG signals from (c) ‘up’ and ‘down’ motions and (d) ‘left’ and ‘right’ motions.

data, threshold values can be chosen in the range of 3–5 $\mu\text{V/s}$, dependent on a user's training data.

Changes of EOG amplitudes according to eye rotation angles (Fig. 4a and b) quantify the sensitivity of two types of electrodes (fractal and conventional). A test subject wears two differential electrodes, positioned 1 cm away from the outer canthus of each eye for concurrent comparison (Fig. 4a). The sensitivity measurement asks the subject to trace a series of circular targets (diameter = 1 cm), located 60 cm away from the eyes. Each target corresponds to 5° changes of eye rotation. Filtered EOG signals in Fig. 4b presents amplitude variations according to eye motions from 0 to 40° . The calculated resolutions are 13.3 ± 0.6 and 11.7 ± 0.9 $\mu\text{V}/^\circ$ for fractal and conventional electrode, respectively. The higher sensitivity from the fractals is explained by considering the signal-to-noise (SNR) related to the skin contact area. The skin-like electrode covers ~ 3.1 cm^2 to maximize the available area on the skin, while the rigid electrode (MVAP II, Newbury Park, CA) including a gel occupies only ~ 0.8 cm^2 , limited by the required adhesive pad to affix on the skin. The direct contribution of the contact area to the signal strength is measured by changing the size of fractals, while the rigid electrode stays intact (Fig. 4c–e). A user wearing both horizontal electrodes focuses on three target locations corresponding to -40° , 0° , and $+40^\circ$ in the horizontal direction (details in Supplementary Fig. S6). The result shows that SNR values decrease as the size of fractals shrinks from full to half and quarter (Fig. 4e; averaged values based on 8 trials); the quarter-sized electrode (contact area: 0.78 cm^2) shows comparable SNR values to the rigid one. A slight DC baseline drift in Fig. 4c and d would come from the low frequency signals with respect to skin potential changes.

Skin assessments by infrared thermography and contact microscopic observation (Fig. 4f–h) capture the advantage of the fractal bioelectrode over the gel-covered rigid electrode. Electrolyte gels on the metal electrode causes an adverse effect (erythema) on the skin by increasing the localized temperature (Fig. 4f; 5 h of skin contact), while the fractal electrode shows a negligible effect even with lamination over 10 h (Fig. 4g). In addition, an adhesive pad, used to mount the rigid electrode, exfoliates the epidermis, which causes pains and skin rashes

(Fig. 4h). Collectively, the comparative assessments demonstrate the novelty of the soft biosensor for a comfortable, long-term usable human-machine interface.

3.3. Classification algorithm

A signal processing algorithm, designed by Matlab (Mathworks, Natick, MA), captures targeted EOG from eye movements of “blink” and “down” (raw data; Fig. 5a). The next step is to process the signals via a third order bandpass filter (Butterworth) at the range of 0.1–20 Hz to remove high frequency noise (Fig. 5b). Afterwards, a series of peak detection methods are implemented (Fig. 5c). The selected start and end positions are pertinent to the signal classification by increasing the detection accuracy. Examples of two sliding windows in Fig. 5d (left: “blink” and right: “down” movement) align the signals in the center since a misalignment results in incorrect classification (details of sliding window classification in Supplementary Figs. S7, S8, and S9). Lastly, the sliding window data are transferred into a linear discriminant analysis (LDA) classifier where a test dataset is compared to the training dataset. The LDA classification plot in Fig. 5e shows a set of representative training data including both correct (o) and incorrect (x) classes.

The classification algorithm includes five features: definite integral, amplitude, velocity, signals mean, and wavelet energy. A common factor in the features is the sliding window indices, identified by t_1 and t_2 . The area under the curve of the filtered signal (Eq. (1)) is acquired using the trapezoidal method. The signal amplitude (Eq. (2)) is determined from the derivative filtered signal, in which A_1 and A_2 are two consecutive peaks surpassing a threshold. A difference between the two peaks explains the order of the positive and negative peaks for each channel. The velocity (Eq. (3)) is simply the amplitude difference divided by the time difference and signal mean (Eq. (4)) is the average of the filtered signals. The Haar wavelet energy transform (Eq. (5)) outputs a set of scaled coefficients ($C_{a,b}$). The absolute multiplication of the coefficients creates the scalogram matrix, which is summed to resolve the desirable wavelet energy feature.

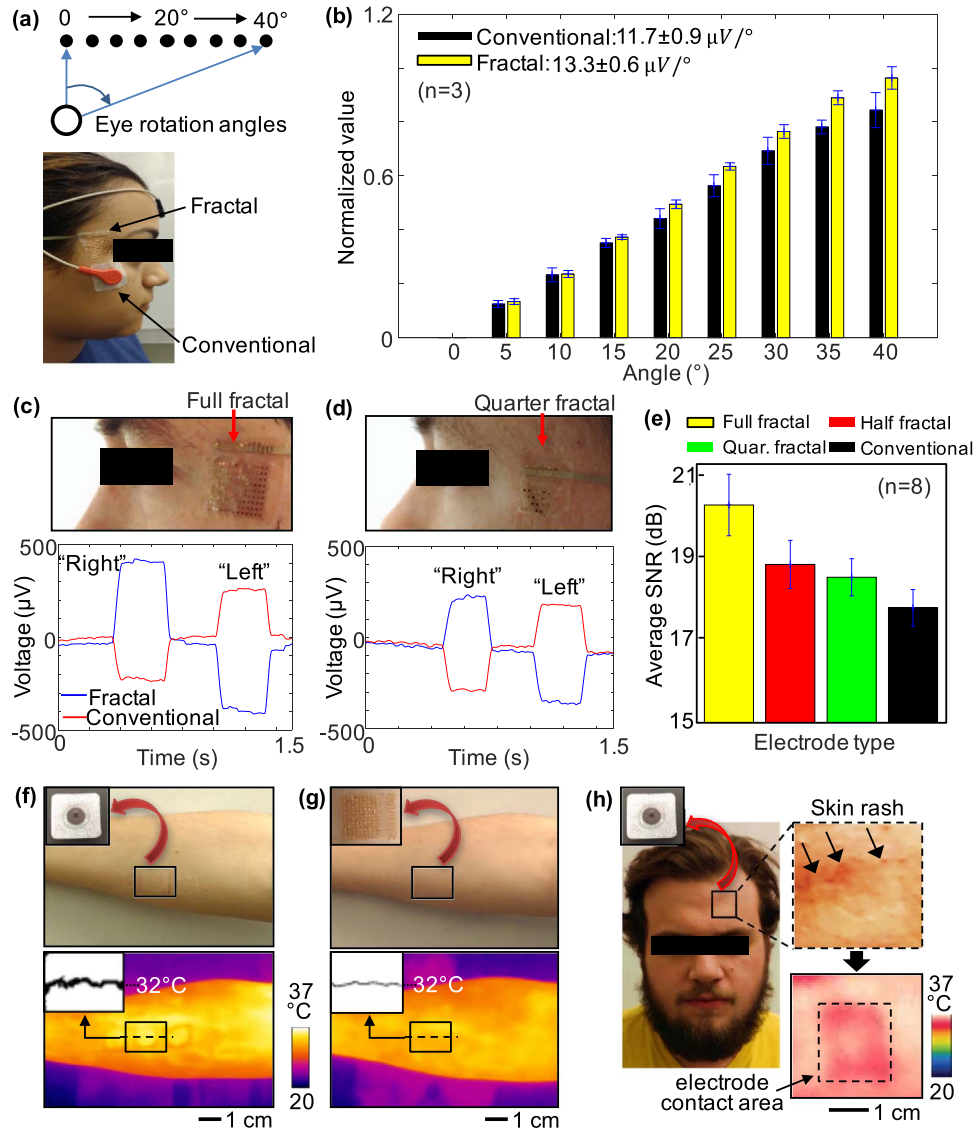


Fig. 4. Comparison of electrode sensitivity and assessment of the side effect from gel electrodes. (a) An experimental setup targeting a series of circles to measure the angle-dependent EOG sensitivity. (b) Normalized EOG signal amplitudes according to the angle change of an eye where black and yellow bars represent conventional and fractal electrode, respectively. Error bars show the standard deviation ($n=3$). (c, d) Photos of fractal electrodes mounted on the skin (conventional electrode is located on the contralateral site) and the corresponding EOG signals comparing the signal strength between fractal and conventional electrodes. The signal strength is dependent of the electrode size; (c) full size and (d) quarter size electrode. (e) Averaged SNR values comparing the size effect of fractal electrodes with a fixed rigid electrode (error bars from $n=8$ with the standard deviation). (f, g) Comparison of infrared thermographs measured with (f) conventional and (g) fractal electrodes to reveal the side effect of the gel contacted to the skin (forearm) for more than 5 h. (h) Photo and thermograph of a gel electrode mounted on the forehead, causing skin rash. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

$$\text{Definite integral} = \int_{t_1}^{t_2} f(t) dt$$

$$\text{Amplitude} = A_{t_1} - A_{t_2}, \quad \text{where } A = \max \left(\frac{d(f(t))}{dt} \right)$$

$$\text{Velocity} = \frac{A_{t_1} - A_{t_2}}{t_1 - t_2}$$

$$\text{Signal mean} = \frac{1}{N} \sum_{t_1}^{t_2} f(t), \quad \text{where } N = \text{number of samples}$$

$$\text{Wavelet energy} = \sum |C_{a,b} * C_{a,b}|, \quad \text{where } C_{a,b} = \int_{t_1}^{t_2} f(t) \varphi_{a,b}(t) dt$$

A simulated program was used to make an accuracy assessment of

the developed algorithm. Confusion matrices in Fig. 6a and b compare the overall accuracy of two types of electrodes based on four classes of eye movements. The averaged accuracy from three subjects shows 91.9% and 94.1% for the conventional (Fig. 6a) and fractal (Fig. 6b) electrodes, respectively (all confusion matrices for 3 different users in Supplementary Figs. S10 and S11). The result presents an enhanced classification accuracy of the fractal electrode, while offering user-comfortable, intimate contact to the skin. The accuracy discrepancy between those electrodes is caused by the limited contact area of the rigid electrode (Fig. 4e). Such an occurrence results in inconsistent signal recording of EOG. In addition, users wearing the rigid electrode expressed slight motion constraints caused by the rigidity of the electrode and adhesive pad, which might limit angular rotation of eyes.

Only the fractal electrodes demonstrate accuracy higher than 98% (average from three users) for 'up' and 'down' motions in the real-time EOG measurement. The maximum accuracy was achieved by optimization of five types of classification features in the LDA classifier (Supplementary Fig.

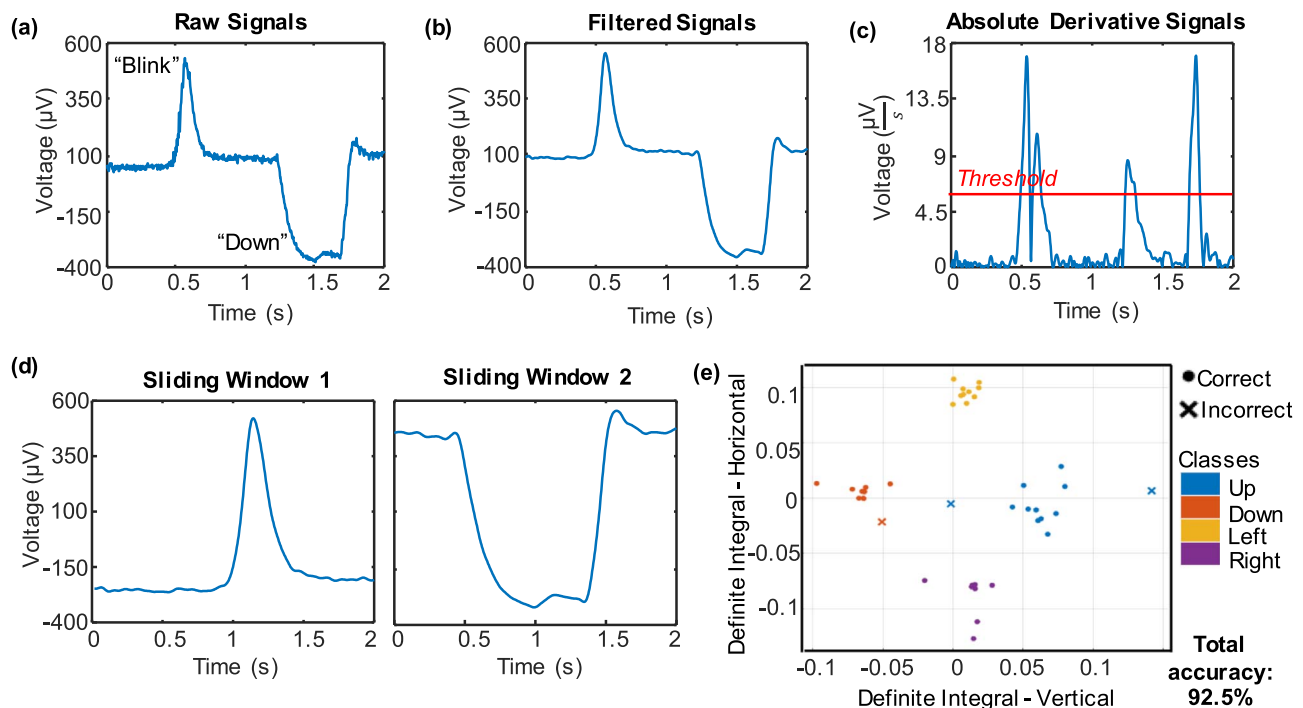


Fig. 5. Signal processing sequence with a LDA classifier. (a) Raw EOG signals measured from eye movements of “blink” and “down”. (b) Preprocessed signals via filtering. (c) Absolute derivative signals to pinpoint target peak signals and apply a threshold boundary. (d) Sliding window algorithm using the detected peaks to parse the dataset into centered signals. (e) Machine learning algorithm using five distinct features from the centered signals and a LDA classifier to distinguish 4 classes of eye movements (up, down, left, and right).

S12), which was used to analyze all EOG signals for confusion matrices in this work. Comprehensive assessments (true positive, false positive, false negative, and true negative) of the classification, summarized in Table S1, supports the enhanced device performance of the fractal electrodes, compared to the conventional setting. We validate our confusion matrix accuracy of each class with a secondary indicator by using the following calculation (Eq. (6)), where TP, TN, FP, and FN refer to true positive, true negative, false positive, and false negative, respectively.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (6)$$

The true positive is determined from the value of each class on the diagonal of the confusion matrix, whilst the false positive is the value of the incorrect classifications of that individual class. The other two measurements resemble the data from other classes not from the observed class. As observed in the comparative accuracy test, the fractal device shows higher successful rates in classification than the conventional electrode. Table S1 shows that one of subjects using conventional electrodes has a high baseline noise that gives low SNR, which attribute to a large number of false positives and false negatives in the “down” and “left” class. The SNR is calculated for each user individually using the first second of the trial as background noise and each sequential motion as the signal. The root mean square (RMS; Eq. (7)) of each window (Supplementary Fig. S13) is used to calculate the SNR and then averaged for each channel of each user to quantify the cause of classification errors (summarized results from 3 users in Supplementary Table S2). Collectively, this quantitative comparison clearly captures the novelty of the soft electrode for persistent, ergonomic HMI applications.

$$\text{RMS} = \sqrt{\frac{1}{N} \sum_{n=1}^N |X_n|^2} \quad (7)$$

3.4. Demonstration of a human-wheelchair interface

EOG signals acquired from the skin-like electrodes control a commercial wheelchair (Invacare™ Pronto, Elyria, OH) that includes

the data acquisition system with real-time classification capability. A microcontroller (Arduino, Adafruit, New York City, NY) and digital-to-analogue converters replace the wheelchair joystick; voltage signals are smoothly transferred to the wheelchair's DC motors and a designed Arduino code adjusts the speed settings to limit motion artifacts from the wires connected to the Bluetooth data acquisition unit (details of the wheelchair setup in Supplementary Note 2 and Supplementary Fig. S14). Four types of eye movements (up, down, left, and right), detected by the soft, fractal electrode around the eyes, control the robotic wheelchair: ‘up’ to go forward, ‘down’ to stop movement, ‘left’ to turn counter-clockwise, and ‘right’ to turn clockwise (Fig. 6c and d). Six consecutive commands operate the wheelchair in real-time to navigate the designed pathway from the position 1 to position 6 (Fig. 6c). Each eye movement is recorded by two sets of vertical and horizontal fractal electrodes. A representative video clip (Supplementary Video 1) captures the entire process of the real-time, human-wheelchair interface. A smart appliance (Android-based tablet; Microsoft Surface Pro 4) provides the concurrent signal display and data saving options to the user.

Supplementary material related to this article can be found online at [doi:10.1016/j.bios.2017.01.044](https://doi.org/10.1016/j.bios.2017.01.044).

4. Discussion

The soft bioelectronic system enables successful measurement of EOG without any use of conductive gels. The computational modeling reveals the excellent mechanical compliance of the skin-like electrode and the experiment agrees well with the computational study. A series of *in vivo* measurement of EOG on volunteers demonstrates the feasibility of the soft bioelectronics for an ergonomic control of a robotic wheelchair. The experimental results present that the fractal electrode shows better performance than the rigid electrode, mounted on the dimpled surfaces of the skin. Overall, the soft bioelectronics shows the potential as a next-generation device for a comfortable, easy-to-use, and wireless control of rehabilitation devices. Areas for further development include an integration of wireless telemetry and powering

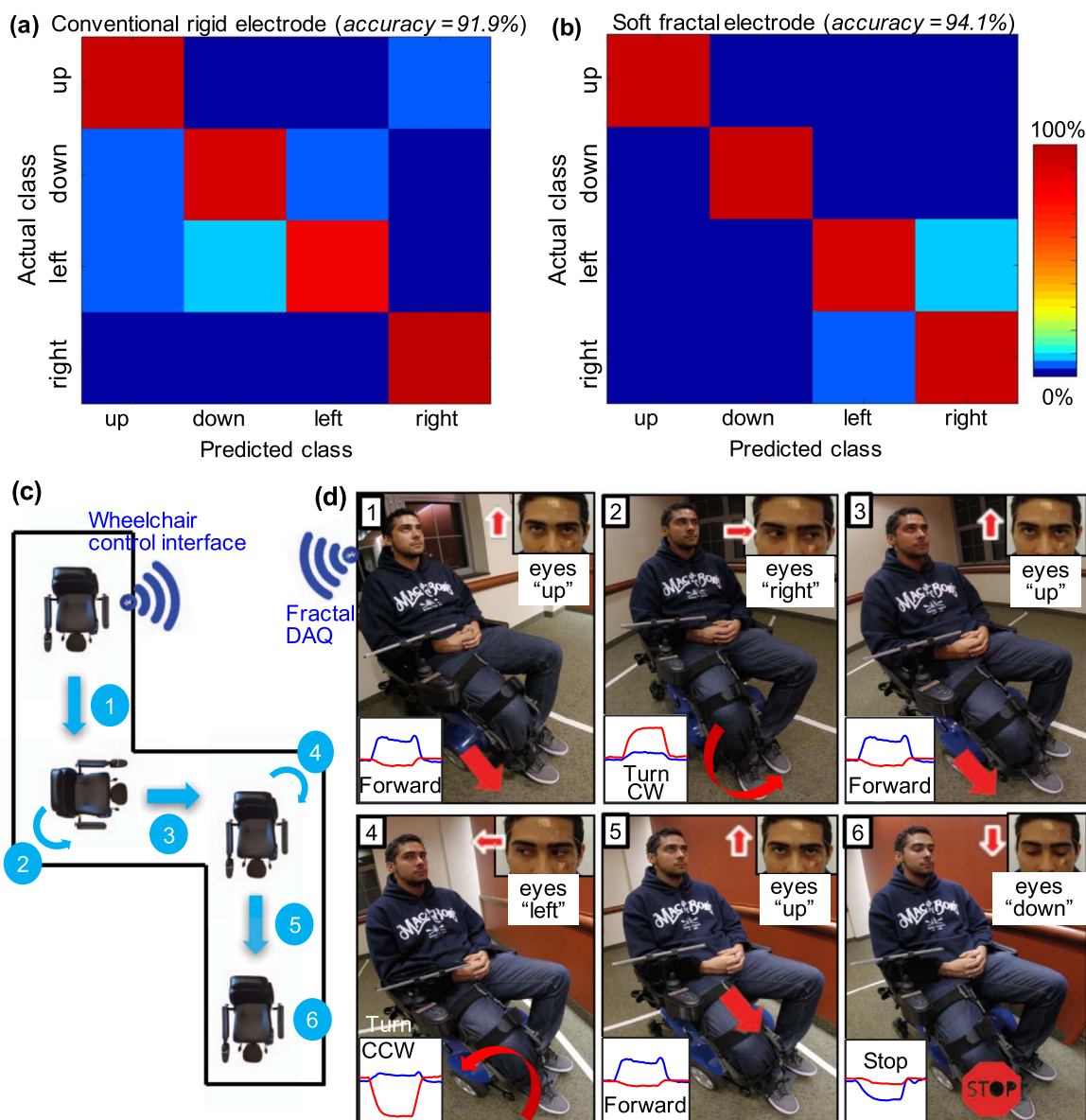


Fig. 6. Demonstration of a human-wheelchair interface via skin-wearable soft electrodes and EOG signals. (a, b) Comparison of confusion matrix from (a) conventional rigid electrodes and (b) soft fractal electrodes; The averaged classification accuracy from three subjects shows 91.9% and 94.1% for conventional and fractal electrodes, respectively. (c) Top view of entire pathways of a robotic wheelchair; classified EOG signals from eye movements are wirelessly transmitted from the fractal electrode/DAQ to the wheelchair control interface via Bluetooth. (d) A series of photos capturing a real-time, wireless control of the wheelchair via eye movements. There are four control commands generated by different eye movements including "up", "right", "left", and "down". Insets show the raw EOG signals in correspondence with the eye movement from a subject.

units in the system. A single device platform will allow high-quality recording of electrophysiological signals for persistent human-machine interfaces.

5. Conclusion

We have demonstrated the feasibility of imperceptible, soft electrodes for a tether-free control of a wheelchair via EOG. The skin-friendly system enables a high-quality recording of EOG from the contoured, dimpled skin, proven by the direct comparison with the conventional electrode. The quantitative thermography and assessment of skin irritations shows additional advantage of the fractal structured electrode. A classification algorithm utilizing multiple features and a LDA classifier distinguishes four classes of eye activities with an accuracy of 94.1% that is higher than the typical rigid system (91.9%). The bioelectronics system incorporating conformal electrodes, real-time data classification, and wireless wheelchair

controller shows a great potential for ergonomic, long-term wearable, and clinically applicable HMI.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at [doi:10.1016/j.bios.2017.01.044](https://doi.org/10.1016/j.bios.2017.01.044).

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