EarFieldSensing: A Novel In-Ear Electric Field Sensing to Enrich Wearable Gesture Input through Facial Expressions

Denys J.C. Matthies[1], Bernhard A. Strecker[1,2], Bodo Urban[1]

[1] Fraunhofer IGD Rostock, Germany, {denys.matthies, bodo.urban}@igd-r.fraunhofer.de

[2] University of Cologne, Germany, bernhard.strecker@uni-koeln.de

ABSTRACT

EarFieldSensing (EarFS) is a novel input method for mobile and wearable computing using facial expressions. Facial muscle movements induce both electric field changes and physical deformations, which are detectable with electrodes placed inside the ear canal. The chosen ear-plug form factor is rather unobtrusive and allows for facial gesture recognition while utilizing the close proximity to the face. We collected 25 facial-related gestures and used them to compare the performance levels of several electric sensing technologies (EMG, CS, EFS, *EarFS*) with varying electrode setups. Our developed wearable fine-tuned electric field sensing employs differential amplification to effectively cancel out environmental noise while still being sensitive towards small facial-movement-related electric field changes and artifacts from ear canal deformations. By comparing a mobile with a stationary scenario, we found that *EarFS* continues to perform better in a mobile scenario. Quantitative results show *EarFS* to be capable of detecting a set of 5 facial gestures with a precision of 90% while sitting and 85.2% while walking. We provide detailed instructions to enable replication of our low-cost sensing device. Applying it to different positions of our body will also allow to sense a variety of other gestures and activities.

Author Keywords

Electric field sensing, body potential sensing, facial expression control, wearable computing, hands-/eyes-free.

ACM Classification Keywords

H.5.2. [User interfaces] – Input devices and strategies.

INTRODUCTION

In Human-Computer Interaction, wearables become increasingly important, which is indicated by the prevalence of smart devices such as glasses or watches. Their tendency to engage the center of attention still hinders the interaction to become truly mobile, though. Therefore, one should reconsider how to access and to interact with technology.

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Figure 1. *EarFS* is a wearable electric field sensing device which enables to sense mobile facial-related gestures. It consists of a) an ear plug plus a reference electrode (a clothes peg that has to be attached to the ear lobe), and b) four sensing shields that are connected to an Arduino which runs on a 9V battery supply and transmits data via Bluetooth.

In 1998 already, Steve Mann stated that wearables should be: *»Unmonopolizing of the user's attention:* […] *One can attend to other matters while using the apparatus,* [while it should be] *unrestrictive to the user.«* [23]

Mann envisions wearable computers to provide situational benefits while not obstructing the user and enabling him for subtle multitasking. In contrast, most of the current interaction concepts still do not provide these qualities. Users are often distracted by current smart devices, such as mobile phones, as they usually require the user's full attention while involving the user's *hands* and *eyes*. For instance, rejecting a phone call or switching between songs on a music player forces the user to take out the device, which unnecessarily demands visual attention and occupies at least one hand. However, *EarFS* enables the user to have these interaction channels available for a potential primary task. This is especially relevant for critical tasks, such as when being involved in traffic. Therefore, we make use of a facial expression control in the manner of microinteractions *»…because they may minimize interruption; that is, they allow for a tiny burst of interaction with a device so that the user can quickly return to the task at hand.«* – Ashbrook [1]

While some facial gestures are also subtle, we potentially enable a shifting of microinteractions to the periphery of our attention [16], which matches the described affordances sketched by Mann. In this paper, we demonstrate such *hands-free* and *eyes-free peripheral microinteractions* with:

- a broad gesture set based on facial expressions, which has been evaluated with various in-ear electrode setups using different wearable technologies (EMG, CS, EFS, *EarFS*);
- a differential amplification EFS (*EarFS*), applicable for wearable computing, that is sensitive enough towards very small changes in electric fields of the human body to detect micro-gestures, such as facial expressions.

RELATED WORK

Facial-expressions, have been widely investigated in the area of affective computing [29]. Affective computing can be described as a system being able to recognize, interpret, process, and simulate human affects. Human affects can be expressed through our faces, which has been extensively investigated starting in the 1970s by Paul Ekman. In one of his fundamental works, he established a facial action coding system (FACS) which is still the ground-truth database for all facial movements and their associated emotional states [8]. Nowadays, we are able to use facial-expressions to determine the frustration level of a user. In terms of technology, two different major setups exist: (1) contact electrodes, which are attached to the face, such as electromyography (EMG) [17] or piezoelectric sensing [36], and (2) proximity sensing, which is often vision-based [13]. Still, utilizing facial expressions for gesture input has not been extensively investigated yet, as we will illustrate.

Facial Expression Control in Medical Context

A major field for application in a medical context is the support of patients, such as those suffering from locked-in syndrome [37]. A common solution is eye tracking (mostly based on vision/camera [20] or electrooculography (EOG) [11]), which can be considered as a facial expression approach. These solutions often include a displayed software keyboard on which the user focuses his vision on in order to enter text [20]. Other use cases include steering a wheelchair by gaze, as already demonstrated by Gips [12], who distributed several EOG electrodes onto the face around the eyes. Furthermore, eye blinks can be used as a binary input in order to provide locked-in patients who are unable to control their eye movements with the ability to communicate. Eye blinks can be detected with several technologies, such as electroencephalography (EEG) [39], or in an optical way [2]. Those text-input systems usually combine a typical P300 speller in scanning mode.

Sensing Technologies for Facial Activity

Technology-wise, there are various ways to detect facial expressions. In the following, we provide a rough overview:

Optical Sensing

The most commonly used technology is a vision-based camera tracking of facial expressions [10]. Obvious expressions, such as frowning, mouth movements, head movements, etc. are detectable with high precision [3,6]. Although visual processing presents one of the most effective techniques, it yields drawbacks: cameras are quickly affected by bad lighting conditions, camera-based systems are usually bulky or stationary, and very small movements, such as tongue gestures, cannot be detected sufficiently.

Electromyography (EMG)

The most rudimentary action is a binary on/off-switch, which can be achieved by measuring an emerging action potential, such as caused by contracting muscles. This has been demonstrated by San Agustin with an EMG headband that detects a frowning or a tightening of the user's jaw [34]. In TongueSee [40], 8 EMG electrodes have been attached to the cheeks and throat to detect tongue muscle movements. This setup enables the user to perform 6 different tongue gestures with an average accuracy of 94%.

Electroencephalography (EEG)

With EEG we usually measure neuro-activity on the cortical surface or within the brain by so called Brain-Computer Interfaces (BCIs). We can use BCIs as a control in two ways: by either utilizing a clean data stream or by using "artifacts" which are created through muscle activity, such as by nose wrinkling, eye blinks, and other facial expressions [27]. Matthies et al. [25] utilize eye winking, ear wiggling, and head gestures, such as nodding and shaking to control a handheld with Emotiv's mobile EEG headset. Since an EEG headset is bulky and hardly applicable in realistic scenarios, an in-ear headset consisting of a hacked NeuroSky EEG system and two gyroscopes was presented, which enables the same gesture set [24]. A similar setup, a foam earplug with two electrodes, has recently been used to classify sleep stages [28]. In our opinion, an ear-plug form factor is the least obtrusive setup.

Electrooculography (EOG)

With EOG Glasses, eye gestures, which are basically tracked eye-movements, could control smart environments such as suggested by Bulling et al. [4]. Other researchers, such as Ishimaru et al. [19], used EOG goggles to roughly identify chewing, talking, eating, and reading with an accuracy of 70%. Manabe et al. attached EOG sensors to a pair of headband headphones [21] and to an in-ear headset [22] in order to sense eye gestures. We believe that placing electrodes into an in-ear headset is rather unobtrusive and apparently offers great sensing potential.

Capacitive Sensing (CS)

Rantanen et al. [30] presented a capacitive sensing glass which is capable of detecting a frowning and a lifting of eyebrows to execute click-events with an average accuracy of 82.5%. In 2013, Rantanen et al. [31] furthermore introduced a face-hugging device which consists of 12 electrodes. They found the activation of four different muscle groups to be detectable with a proximity sensing. While these results are impressive, wearing a face-hugger is rather obtrusive since it almost covers the whole face.

Electromagnetic Sensing

In 2006, Fagan et al. [9] placed seven magnets on the lips, teeth and tongue that cause a significant change in the magnetic field when performing mouth-movements. 6 Dual axis magnetic sensors were mounted on a prepared pair of glasses, which enabled a detection of 13 phonemes with an accuracy of 94%, and 9 words with an accuracy of 97%. Even though the physical setup is quite bulky and obtrusive, the results are impressive. In 2014, Sahni et al. [32] attached only one magnet onto the tongue and utilized the built-in 3 axis magnetometer of Google Glass plus an in-ear piece measuring the optical ear canal deformations in order to detect tongue and jaw movements. They report to be capable of distinguishing 11 sentences with 90.5%.

Prior research reveals that we face a trade-off between having an obtrusive hardware setup providing quite meaningful features versus unobtrusive hardware setups that are limited in features and recognition precision. However, we believe that it is possible to find a more advantageous solution compared to those presented before – a device that is unobtrusive (such as an in-ear plug) and that still provides a reasonable feature set.

EARFIELDSENSING

We present *EarFieldSensing (EarFS)*, an improved electric field sensing device capable of sensing electrical changes in the ear canal by an in-ear electrode setup. We think, hiding a sensing device in a subtle ear plug is less obtrusive than other approaches demonstrated in literature. Also, using facial expressions for input enables for *hands-free* and *eyes-free* interaction, which is safe when operating devices, such as a smartphone, while being involved in traffic.

Contribution

As an essential part of this work, we developed an improved electric field sensing for which we provide technical details to enable reproduction of our sensing technology.

To gain insights into the performance level, we conducted a lab study to compare previous technologies with a gesture set of 25 facial-related gestures. Compared technologies:

- Electromyography – EMG (*Shimmer3*[1]),
- Capacitive Sensing – CS (*FDC2214 Texas Instruments*[2]),
- Electrical Field Sensing – EFS (*hacked OpenCapSense* [14]),
- Improved Electrical Field Sensing – *EarFS*.

A comparison of technologies in a stationary setup can reveal theoretical performance differences, but does not reflect reality, such as when the user freely moves around. Therefore, we conducted a second study in which we present more insights into performance differences in a mobile context. As a result, we found *EarFS* (*see Figure 1*) to outperform other evaluated electrical sensing technologies when it comes to the recognition of facial-related gestures in mobility while walking.

[1] Shimmer3 EMG Unit:
http://www.shimmersensing.com/images/uploads/docs/Shimmer3_ECG_EMG_Specification_Sheet_Revision_1.7.pdf

[2] Texas Instruments FDC2214:
http://www.ti.com/lit/ds/symlink/fdc2214.pdf

Background

In this subsection, we describe the reason of being able to sense various facial muscle movements and head gestures by placing a sensor piece into the ear canal.

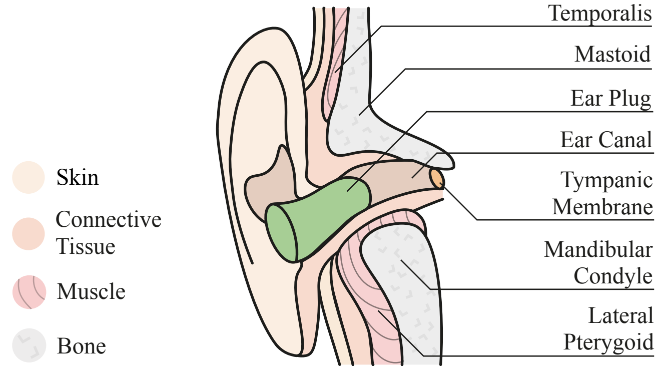

Figure 2. An ear plug enables the experience of deformations and changes in an electrical field while resting in the ear canal.

When talking of the ear canal, we mean the tunnel between Mastoid and Mandibular Condyle (*see Figure 2*). Facial expressions, such as yawning, cause an opening of the mouth which is triggered by a contraction of the Lateral Pterygoid. This process causes the Mandibular Condyle to slide forward and thus a tiny void is created, which is then filled with the surrounding tissue. A change in volume and deformed tissue creates a very different electrical field, which is detectable. Even eye movements and head movements are perceivable, although the electrical change is comparably small. As we quickly figured out, movements of the jaw are quite easily perceivable. Other muscle activities, such as raising eye brows, are apparently triggered by other muscle groups (e.g. Frontalis) located on the forehead. Still, we can sense these activities in the ear, because many facial muscles are connected with the Temporalis, the biggest muscle of the head, which forwards mechanical and electrical artifacts towards the ear canal.

Performing a manual self-test: putting the pinky inside our ear, while executing facial expressions, lets us sense these deformations.

Nature of Signals

In a spot so small as the ear canal, we measure compound electrical activity (white sensor noise, environmental noise, potential changes from muscle activity, characteristic signal peaks from ear canal deformations, and very tiny signals from neural activity such as from brainwaves). As mentioned before, ear canal deformations inducing changing electrode-skin contact play a major role. As a matter of fact, increasing skin-contact gradually decreases the electrode input impedance and leads to a transition in signal contributions, e.g. the action potentials' share of the total signal increases.

Mobile Sensing of Facial Expressions

The application of facial expression recognition via an in-ear-positioned electric field sensing is challenging and far more delicate than just recognizing hand/arm gestures. This is due to the electric field changes that are brought upon by facial muscle movements, which are much smaller in magnitude. Especially in a mobile situation, artifacts caused by walking are crucial. Nevertheless, we envision a facial gesture recognition in mobile scenarios that works independently from side-actions, such as walking, running, biking, jumping and sitting. For the example activity of walking, the user's body experiences a periodically changing capacitive coupling to ground, which substantially impacts an electric field sensing on any part of the human's body. Unfortunately, it is hard to anticipate the frequency of the signal caused by walking or running since speed levels are likely to change when the user, for example, hurries to catch a bus. Therefore, it is hard to target specific frequencies for filtering out. Moreover, these frequencies are rather low and can typically range from anywhere in between 1 to 5 Hz, which are the same frequencies that carry information of facial gestures.

Technical Solution

The first step of *EarFS* is to isolate electric field changes brought upon by facial gestures as effectively as possible while simultaneously reducing environmental artifacts, such as caused by walking. As mentioned before, an option would be to filter out periodical signals which are reappearing over a longer period of time. However, this does not solve the problem since parts of the unwanted artifacts may also overlap with signals stemming from facial expressions. A simple filtering of artifacts would possibly erase signals of facial gestures as well, because they are too marginal in amplitude in comparison to the artifacts' signal strengths. In fact, as long as artifacts occur on the signal we cannot amplify these comparably small facial gestures. Otherwise, the operational amplifiers would saturate and low magnitude facial gestures are prone to disappear in the signal. Therefore, we eliminate these high magnitude artifacts early on by isolating them beforehand and subtracting them from the original signal with a dual electrode approach as described next.

Differential Amplification using a second Electrode

Our solution uses a second "reference" electrode that needs to be placed relatively far away from the face. We then feed a difference / instrumentation amplifier with the two signals, the one gathered from the reference electrode, and the other from the in-ear electrode. This way, common-mode signals stemming from walking artifacts, which are similar on the whole body, are likely to be filtered out or at least substantially reduced. It is important to note that the placement of the reference electrode is crucial, because any limb movements may affect signals. By attaching the reference electrode to the waist, for example, the arm would create a change in electrical field while nearing or passing the reference electrode when the user walks. An ideal place

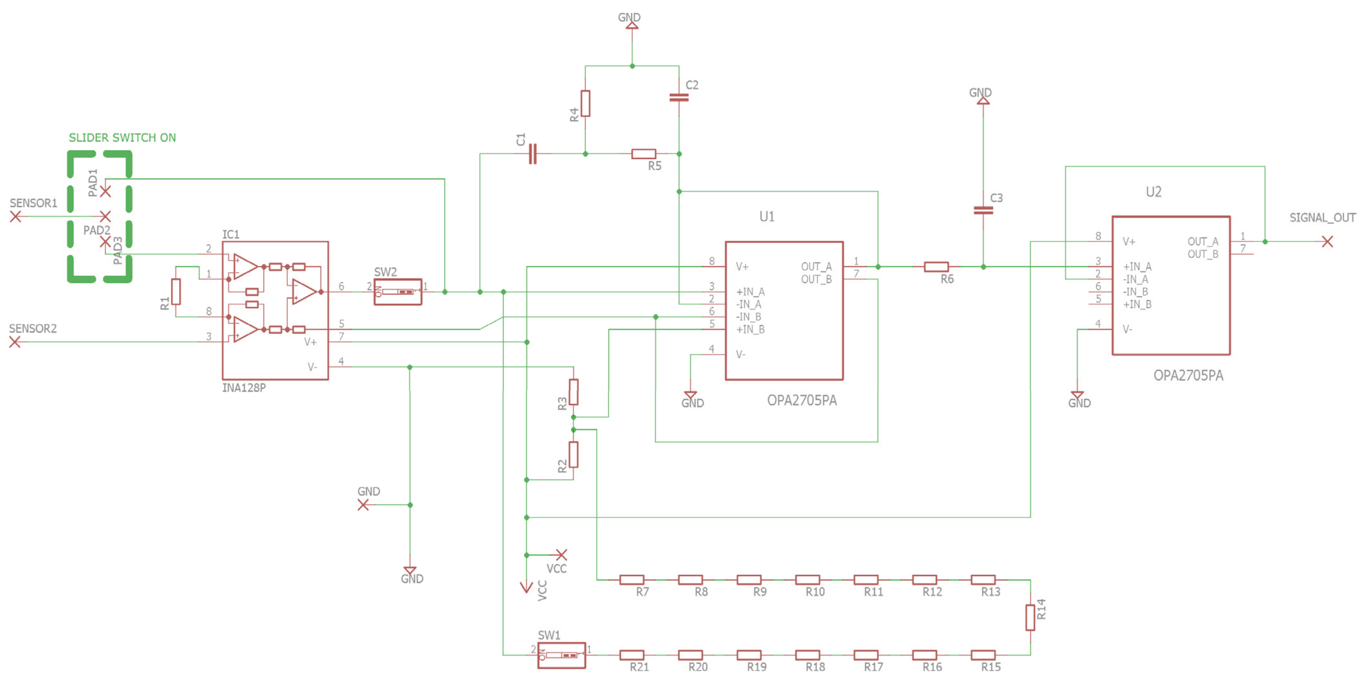

Figure 3. Schematic of the *EarFS* prototype, supporting both (1) single electrode and (2) differential electrode mode. In single electrode mode, to cover electric field changes of both polarities, a large pull-up/-down resistor is used to elevate the signal level of the earplug-electrode to half the supply voltage. We use fifteen 10 MΩ resistors (R7-21; 10 MΩ resistors are more common than 150 MΩ ones) in series between a simple voltage divider (|R2|=|R3|) and the signal path in order to pull slowly enough for detecting electric field changes. In differential mode, the INA128P instrumentation amplifier filters out environmental noise by common-mode rejection. The difference in voltage between the earplug- (SENSOR1) and earlobe-reference (SENSOR2) electrodes is expected to be rather small, so it is amplified by a factor of 5001 (R1 = 10 Ω), which is well within the gain-range of the INA128P (10k is max). Also the output signal of the INA128P is elevated to half the supply voltage. A band-pass filter (C1 = C2 = 4.7 nF, R4 = 1.8 MΩ, R5 = 390 kΩ) reduces power-hum (50 or 60 Hz) by negatively feeding it back into the signal. Based on application context, C3 & R6 can be used to implement a low-pass filter of choice. Please note: band-pass- & low-pass-filtering are not compulsory.

of the reference electrode would be a relatively stationary position that is far away from the face to get a significantly different electric potential sensing compared to the electrode placed in close proximity to the face. As a matter of fact, the electric field strength declines exponentially with distance, so the reference electrode can also be placed close to the face, such as at the backside of the neck, spine, shoulders, or at the ear lobe. While both electrodes accumulate artificats, the in-ear electrode yields a sufficiently different signal containing facial gestures that remain when subtracting both signals from each other and become visible when amplifying the subtracted signal. To our knowledge, previous work did not use differential amplification in this context before, and we seldom encounter it in HCI applications yet.

Implementation

An electric field sensing circuit was designed (*see Figure 4*), which can be used similarly to common EFS sensing circuitry, but also offers signal acquisition by amplifying a differential signal from two separate electrodes. In this mode, the *differential instrumentation amplifier* reduces and even cancels out most environmental noise.

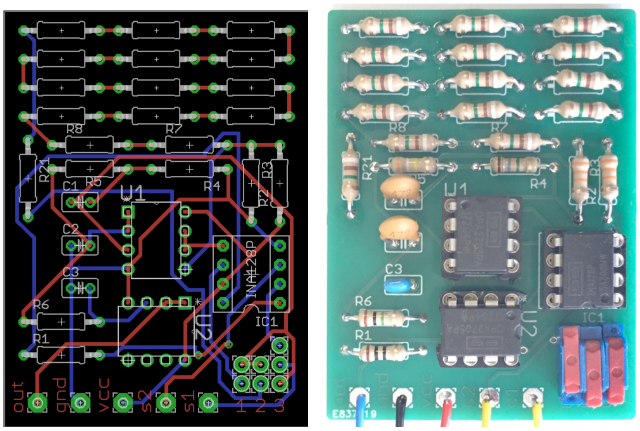

Figure 4. Left: Eagle PCB layout. U1, U2: OPA2705PA; IC1: INA128P. Right: Final *EarFS* PCB. Switches offer two modes (1) ↑↓↓ single electrode / antenna and (2) ↓↑↑ differential electrode / antenna setup.

In order to let other researchers replicate our hardware, we additionally provide the schematics of our sensing circuit (*see Figure 3*). Once the hardware is built, one can easily connect the Signal-Out Pin to the Analogue Input Pin of any microcontroller board, such as A0 on an Arduino board. As most microcontroller boards, our sensing device also runs with 5V DC.

Single Electrode Mode and Differential Mode

Three switches have been included in the circuit to allow the user to choose between (1) single-electrode / antenna setup and (2) differential electrode / antenna setup. (1) The slider switch in Figure 3's top left corner connects PAD2 to PAD1, SW2 is off and SW1 is on. (2) All three switches are being reversed – the slider switch connects PAD2 to PAD3. A pull-up/down resistor was included for single-electrode (S1) usage, so that electric field signals will return to the baseline of half V_{CC} when no change in electric fields is present. Thus, only movements that create field changes are perceivable. Concerning the differential configuration, the instrumentation amplifier was biased to half V_{CC}, so that electric potential changes of either polarity can be sensed.

STUDY 1: TECHNOLOGY PERFORMANCE

In this section, we evaluate the detection of facial-related gestures by a variety of electric sensing technologies.

Research Questions

The goal of this study was to gain an insight into the following research questions while trying to keep all variables as constant as possible (e.g., testing all setups by the same user, only testing one session per day):

Q1: How does our technology perform compared to other electric sensing technologies?

Q2: What would be the best electrode setup providing the highest accuracy rates for each technology?

Q3: Which gestures are the top 5 performing ones with the given technology?

In study 1, we were *not* yet interested in finding out about varying performance levels across users, nor the applicability in mobile scenarios. Therefore, we forfeited on testing all possible setups with multiple users in mobility.

Task and Procedure

To answer these research questions, we performed an extensive study in which we recorded 14,000 gestures (= 7 ear plugs * 2 un/covered * 25 gestures * 10 repetitions * 4 sensing technologies) from a single user. To avoid fatigue effects, we split the recordings into several sessions, which included 1 technology with all earplugs in sequential order. 25 gestures * 10 reps were recorded with each setup before insulating the earplug or taking the next one. Each gesture was recorded in a time window of 1.25s. To prevent invalid data distortion, the earplug was not rearranged during sessions. When the user was not sure about the correct execution, he was enabled to record an additional repetition. The test subject trained steady gesture execution beforehand and triggered the recording manually after being randomly presented with a gesture left in the pool of 250. A complete session contained 250 * 7 = 1750 gestures.

Facial Gesture Set

We compiled a set of 25 facial- and head-related gestures (*see Figure 5*) to compare all technologies based on their performance level. The gesture set covers a broad spectrum of which we are aware that not all of them are subtle or socially acceptable. The set was chosen for straightforward repeatability while it includes gestures involving various muscle groups. The contraction of different muscle groups presumably leads to a distinctive signal in order to identify gestures. Apart from typical gestures, such as 'eye-wink', 'smile', and 'protrude-tongue', simple speech was included as well, because speech is performed highly automated due to it being easy to memorize.

Figure 5. With a set of 25 gestures (including a default gesture) we evaluated four different technologies (EMG, CS, EFS, *EarFS*) .

Apparatus: Electrode Ear Plug

We prepared 7 earplugs which are made out of polyurethane foam and go by the name of OHROPAX Color[3] (*see Figure 6*). #1 is a single electrode wrapped around the earplug. #2h - #4h are two to four increasingly smaller electrodes wrapped horizontally around the earplug in a similar fashion. #2v - #4v have electrodes in decreasing sizes, which are vertically placed alongside the earplug. Accordingly, #2v has two electrodes, #3v has three, and #4v has four electrodes mounted on the earplug.

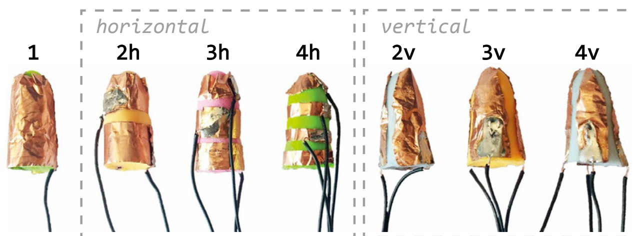

Figure 6. With 7 different electrode layouts we evaluated each technology. For us, it seemed natural arranging the electrodes lengthwise and widthwise alike with varying partitions while we used them blank (as shown), and covered.

All electrodes were cut out from copper foil, soldered to the connecting cables, and subsequently glued onto the earplugs with Pattex superglue. All 7 setups have been tested both with blank electrodes and while being covered with the cut-off tip of a common condom. The lubricant was thoroughly washed off beforehand, and remaining moisture left on the latex was dried off before conducting experiments.

Apparatus: Electromyography (EMG)

EMG is the most common technology to measure *action potentials* stemming from muscle activity, which is usually done invasively by needle electrodes. Nonetheless, the superimposed voltage is also detectable on the surface of the skin while it still shows ranges of up to -100mV [18]. In an interaction scenario, surface electrodes on the skin are typically used [33] for measuring electrical potentials through a relatively thick layer of skin and fat. For classifying gestures one can use not only a clean signal, but also noise [26] and accumulated movement artifacts [24], which occur in the ear canal when performing gestures.

Figure 7. Shimmer3 ECG/EMG Bluetooth device, configured in EMG mode.

In our study, two Shimmer3 EXG units[1] were connected via Bluetooth to a computer (*see Figure 7*). The Shimmer Android/Java API was used to configure the EMG units and to establish communication. A suggested digital filtering (50 Hz noise cancellation and low-pass filtering for signal smoothing) was also implemented. The earplug electrodes were connected to a single channel each in the following way: The earplug-electrode was connected to the positive differential input of the Shimmer3 EMG channel and a clothespin-mounted copper foil reference electrode was clipped to the earlobe of the opposite ear that the earplug was worn in. The reference electrode was connected to the REF input of the up to three Shimmer3 units and connected to all negative differential inputs of active channels.

Apparatus: Capacitive Sensing (CS)

Capacitance describes a body's ability to store an electrical charge when a voltage is applied. The higher the electrical charge a body can store, the higher its' capacitance. As a matter of fact, the human body's cells also have the ability to store electrons and thus a negative electrical charge. Depending on the body part, we can speak of an overall capacitance varying between 50 and 150pF [35]. Excited cells, which accumulate a certain amount of electrons, create the change in capacitance. While this capacitance can be measured invasively, we can also measure it on top of the skin or in distance, such as with an isolated earplug electrode. A typical CS measures the charging time of an electrode. This is also referred to as *loading mode* [38].

[3] OHROPAX Color: http://www.ohropax.de/produkte/color.html

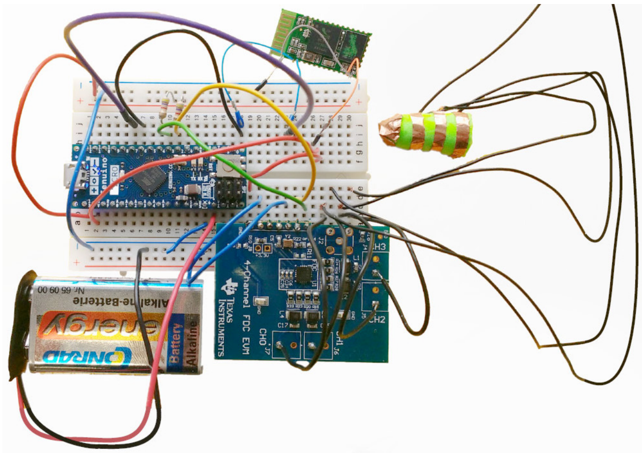

Figure 8. The Capacitive Sensing shield FDC2214 EVM from Texas Instruments was plugged to an Arduino board transmitting the raw data via a Bluetooth 2.0 modem.

The FDC2214[2] also uses capacitive sensing in *loading mode*. We connected it to a Genuino Micro streaming all raw data via an HC05 Bluetooth modem (*see Figure 8*). It is essential to use a battery plus a wireless transmission to avoid irregularities, such as a varying capacitive ground coupling triggered by other hardware components that may also be connected to the computer. To measure each of the four channels in turn, 512 oscillations were used to determine the momentary frequency of the LC oscillator circuit compared to the EVM board's 40 MHz oscillator. After each channel switch, the first 128 oscillations were not considered to allow for the frequency to stabilize.

Apparatus: Electrical Field Sensing (EFS)

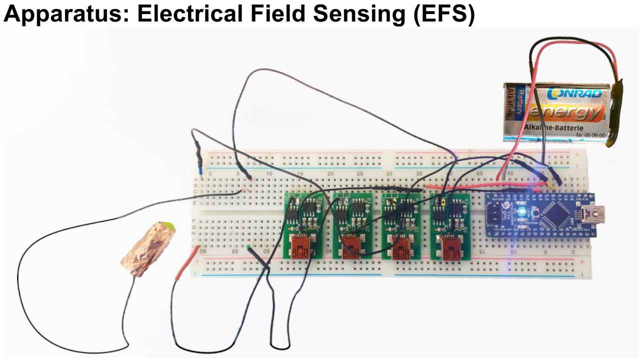

Figure 9. We "hacked" four Loading Mode capacitive sensors from OpenCapSense [14] to act like an Electric Field Sensor.

Electric fields are ubiquitous and exist due to the static electricity of our surroundings. Besides everyday objects, also the human body carries several small electrical fields. Fluctuations in electric fields quickly occur when moving the human body or other charged objects. While we can utilize electrical field changes for a gesture recognition [7], it is also perfectly suitable for an intended facial expression recognition. However, factors such as ambient noise and baseline drift are the most cumbersome obstacles that gesture recognition and classification endeavours face. Anyhow, all that is needed to implement electric field sensing is basically a "passive" electrode (i.e. antenna) with an operational amplifier connected to an analogue-to-digital converter (ADC). To compensate for noise, such as power hum, low-pass filters may apply between op-amp and ADC.

Our EFS setup consists of four „hacked" OpenCapSense *loading mode* sensors, which basically consist of an operational amplifier and an astable Multivibrator that is usually used for a capacitive measurement. However, we only utilize the op-amp whose positive input is connected to the electrode. The op-amp's output is connected to the analogue input of an Arduino Nano (*see Figure 9*), which serves as an ADC and transmits the raw data. It should be particularly noted that here, the op-amps are not connected to an external power source. However, they still output discriminable voltage based on the acquired earplug signal, which also serves as a power supply in a way that the electrode is wired to the op-amp pin right next to the negative supply pin, facilitating a discriminable voltage between the negative and positive op-amp supply pins.

Apparatus: *EarFS*

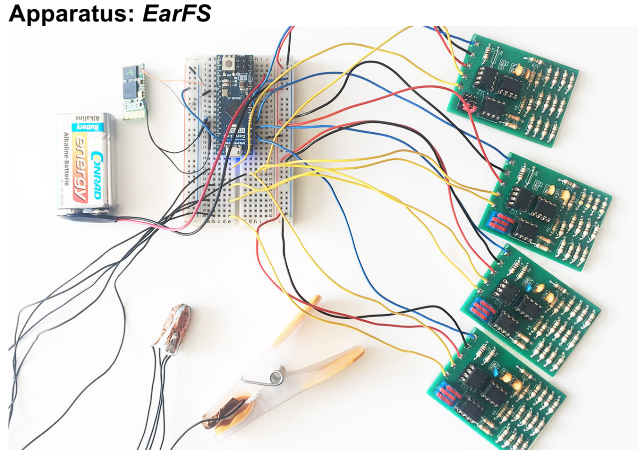

Figure 10. Four EFS shields are connected to an Arduino in order to use a four-electrode ear plug. The data is being streamed via a Bluetooth 2.0 modem to a computer, while the prototype is powered by a 9V battery.

Fluctuations in ambient electric fields can originate both from negative and positive charge balance and thus, a standard single supply op-amp design like seen before would be doomed to miss one of the polarities. Therefore, we introduce a second DC-voltage, keeping the antenna voltage at a proportionally steady and elevated level. It is wise to choose a DC-voltage of half the op-amp's supply voltage, since in this way, incoming antenna signals can deviate from the baseline voltage in the direction of both electrical polarities. When no changing electric field is present, a relatively large resistor pulls up/down the antenna voltage to the baseline voltage eventually. It should be noted that larger resistors cause longer latencies. The addition of such a pull up/down resistor with its tendency to pull the antenna voltage back to half the V_{CC} voltage is the reason that only movements and changes are measurable. In addition, we added a reference electrode (*see Figure 10*) to eliminate extrinsic changes in electrical fields with a differential amp.

Electrodes		EMG (Shimmer3)			CS (FDC2214 Texas Instruments)			EFS (hacked OpenCapSense)			EarFS		
		Average Accuracy (TP)			Average Accuracy (TP)			Average Accuracy (TP)			Average Accuracy (TP)		
blank		all 25	n≥50%	top 5	all 25	n≥50%	top 5	all 25	n≥50%	top 5	all 25	n≥50%	top 5
	1	19.2%	-	-	1.6%	-	-	1.6%	-	-	3.2%	-	-
horizontal	2	11.7%	-	-	16.8%	-	-	35.1%	-	-	5.2%	-	-
horizontal	3	4.8%	-	-	30.8	-	-	40.8%	-	-	8.8%	-	-
horizontal	4	12.8%	-	-	43.2%	-	-	39.5%	-	-	13.2%	-	-
vertical	2	**30.8%**	**4**	**84%**	12%	-	-	43.6%	-	-	13.6%	-	-
vertical	3	10.4%	-	-	34.4%	-	-	**52%**	**11**	**94.5%**	12.4%	-	-
vertical	4	19.2%	-	-	**48.4%**	**13**	**90%**	49%	-	-	**32%**	**5**	**90%**
covered													
	1	**11.6%**	**0**	**64.4%**	9.6%	-	-	4%	-	-	**5.6%**	**0**	**20%**
horizontal	2	5.6%	-	-	**38%**	**11**	**84%**	4.4%	-	-	2.8%	-	-
horizontal	3	6.4%	-	-	35.2%	-	-	5.2%	-	-	4%	-	-
horizontal	4	6.8%	-	-	21.6%	-	-	4.4%	-	-	4.8%	-	-
vertical	2	6.2%	-	-	22.4%	-	-	3.6%	-	-	4%	-	-
vertical	3	6%	-	-	29.6%	-	-	**7.6%**	**1**	**20%**	5.2%	-	-
vertical	4	3.2%	-	-	28%	-	-	5.6%	-	-	2.4%	-	-

Table 1. Performance levels using a J48 DT (C4.5 algorithm). For each technology we can find three columns: 1) true-positive (TP) rates of the complete gesture set, 2) number of gestures yielding at least 50% TP, and 3) TP score of a reduced top 5 gesture set.

Signal Gathering and Data Processing

The aforementioned electrode-earplugs have been combined with all four technologies while we recorded each gesture with a sample rate of 200 Hz and a window-size of 256. Then, we computed 46 state-of-the-art features found in literature on all raw data recordings. Because we are not aware of any library providing them, we implemented them by hand in Java. For analysing the data, we use the Weka data mining tool [11] in order to gain an impression on the performance using five state-of-the-art classifiers (*Bayes Net* - BN, *K-nearest neighbours* - Ibk, *J48 Decision Tree* – J48, *Random Forest* - RF, *Sequential Minimal Optimization* - SMO) while performing a stratified 10-fold-crossvalidation. We have chosen this method, because conducting a manual leave-$k_{instances}$-out method on our huge dataset (14.000 instances) is extremely time consuming and beyond practicality. Nevertheless, we had a quick look (k=5) at a single session (*EarFS*, 4-vertical) and could perceive a marginal accuracy drop of Δ= -1.6 %.

Results

Before presenting the result, it is important to note that we are talking of a theoretical performance level. To make a sophisticated statement on realistic recognition rates, one should have tested users n>10 in ambiguous environments (including critical environments with high level of electric noise, e.g. a server room). In this paper, we decided to keep experiments within reasonable boundaries and share early results of the exact composition with the community.

Classifier & Feature Selection

In order be able to answer our research questions, we first determined the "best" classifier. We compared all five classifiers (BN, J48, Ibk, SMO, RF) by means of an independent samples one-way ANOVA, but which showed no significant differences for EMG ($F_{4,30}$=1.14; p<.357); CS ($F_{4,30}$=0.58; p<.680); *EarFS* ($F_{4,30}$=0.06; p<.993). Nevertheless, the EFS showed strong significant differences ($F_{4,30}$=17.96; p<.0001). Conducting a Tukey HSD Test revealed the J48 (M=43.35; SD=6.25), BN (M=43.47; SD=5.50), and RF (M=37.57; SD=12.12) to perform better than the Ibk (M=20.30; SD=7.53; p<.01). Moreover, the J48 and BN were deemed to significantly perform better than the SMO (M=31.86; SD=8.29; p<.05). Beholding the mean performance over all technologies, we can perceive the J48 and the RF to perform quite well. Because the J48 is most computationally inexpensive and a rather simple classifier, we selected it for further investigations.

Across all best setups, top 5 meaningful features, selected by a *Greedy Stepwise (forwards)* algorithm [5], include: *spectralEnergy, spectralFlux, spectralSignalToNoiseRatio, minMaxDifference, and pairDifference*.

Answering Research Questions

Q1: As seen in *Table 1*, *EarFS* performs similar to other electric sensing technologies, comparing their best setups. A one-way ANOVA ($F_{3,27}$=193.91; p<.001) showed *EarFS* (M=32%) to perform equally to the EMG (M=30.8%) and EFS (M=52%) equally to CS (M=48.4%). Still, a Tukey HSD (p<.01) reveals both EFS and CS to perform significantly better among EMG and *EarFS*.

Q2: The electrode setups providing best performance are indicated in *Table 1*. Generally, we can say that non-insulated, vertically arranged electrodes perform better, because these are more sensitive towards ear-canal deformations (changing skin / electrode contact). Since the vertical electrodes are distributed in circular fashion, an increase in their number leads to higher spatial resolution inside the ear canal.

Q3: We determined a top 5 gesture set for the best setup of each technology *(see Table 2*). In fact, the recognition rates look quite reasonable and foster curiosity: EMG (M=84%), CS (M=90%), EFS (M=94.5%), and *EarFS* (M=90%).

	EMG (Shimmer3)	*CS (FDC2214)*	*EFS (OpenCS)*	*EarFS*
1	eyes-left	head-back	chin-on-chest	eye wink
2	head-back	open-mouth	eye wink	head-right
3	head-left	protrude-tongue	say-u	open-mouth
4	say-e	eye-brows together	eyes-down	say-sh
5	smile	say-a	head-right	smile

Table 2. Top 5 gestures for the best technology setup. We chose to select the number of 5 gestures, because the ability to remember shortcuts, such as gestures, dramatically decreases with larger numbers than 7 in a real scenario. Following cognitive engineering, 5 is also a suggested maximum.

Summary

The analysis revealed all technologies to be capable of a facial-gesture recognition by measuring them inside the ear canal. In our opinion, the classification accuracy is astonishing considering the broad gesture set of 25 facial expressions. Two characteristic 'clusters' of confusions occurred among the gestures. One cluster can be found around gestures of the *Oculi*, and the other around the *Lingua*. Because these gestures are similar in type, the confusion between them is most likely connected to their actual similarity.

STUDY 2: WEARABLE PERFORMANCE

Since the first study was performed in a very controlled environment, we thought it may be interesting to see whether our evaluated technologies could be employed as a wearable technology in a mobile context as well.

Study Setup

Therefore, we conducted an experiment with 3 participants, aged 26, 29, and 30 years. While each technology was tested with all users, the task was to perform all top 5 gestures of each technology (*see Table 2*) with its' best earplug setup for 10 times in a random order.

There was a marginal training phase in which the user had the chance to perform each gesture once or twice. After the study started, the study leader was shouting each gesture out loud while he was triggering the recording. To test the technologies' limits, we instructed each user to randomly walk around within a spot of 10 x 10 meters in a medium-sized lobby with stone-tiled floor.

In summary, we recorded 600 gestures (3 users * 4 technologies * 5 gestures * 10 repetitions). We again calculated 46 state-of-the-art features from the raw data and used a J48 Decision Tree while performing a stratified 10-fold-crossvalidation.

Hypotheses

Since we already know about the theoretical performance in a stationary context, we can establish these hypotheses:

H1: *EarFS* will perform equally or better than other technologies, because it works with a differential amplification. Hence, it should be more robust towards influences from external noise in mobility.

H2: All other technologies will experience a substantial drop in accuracy, because they are heavily affected by environmental noise occurring while moving.

Results

The results confirm our assumption. *EarFS* performs well in context of mobility. *Table 3* shows the performance of *EarFS* in a confusion metrics accumulated over all users:

a	*b*	*c*	*d*	*e*	<- classified as
96.7%	3.3%	-	-	-	*a = eye wink*
-	89.7%	3.4%	-	6.9%	*b = head right*
3.3%	-	80.0%	16.7%	-	*c = open mouth*
-	-	13.3%	80.0%	6.7%	*d = say SH*
-	3.3%	6.7%	10.0%	80.0%	*e = smile*

Table 3. Accumulated confusion matrix of all users showing overall performance of the *EarFS* using a J48 decision tree.

Answering Hypotheses

H1: Looking at *Table 4*, we can see that over all users, *EarFS* (*M*=85.2%) achieves a substantially higher mean accuracy than EMG (*M*=76.7%) and CS (*M*=79.9) when the user walks around randomly. A one-way ANOVA ($F_{3,8}$=6.27; p<.02) also found statistical differences in terms of performance level. A Tukey HSD test confirmed our technology to significantly outperform EFS (*M*=73.7%). Therefore, we accept this hypothesis: *EarFS* is more robust towards external noise in mobility and yields higher accuracy while it even significantly outperforms EFS.

EMG (Shimmer3)	*CS (FDC2214)*	*EFS (OpenCS)*	*EarFS*	
84%	90%	**94.5%**	90%	*sitting*
76.7%	79.9%	52.8%	**85.2%**	*walking*
80.4%	85%	73.7%	**87.6%**	∅

Table 4. Overall performance (True-Positive rates) of study 1 (sitting) in comparison to study 2 (walking). The setup: top 5 gestures, preferred electrode setup, J48 classifier.

Incidentally, it is even more surprising to see that EFS initially outperformed *EarFS* while sitting. One reason would be because OpenCapSense is a more integrated PCB and does not suffer from small distortions of loose wires like *EarFS*. However, as shown before, it is bound to underperform while walking, since it is not supporting differential measurements.

H2: Running a simple *t*-Test confirms $CS_{walking}$ (*M*=79.9%) to be significantly worse than $CS_{sitting}$ (*M*=90%). Also, $EFS_{walking}$ (*M*=52.8%) is performing significantly worse than $EFS_{sitting}$ (*M*=94.5%). We can also see a decrease from $EMG_{sitting}$ (*M*=84%) to $EMG_{walking}$ (*M*=76.7%). However, while EMG is generally performing low, it is not yet statistically different. *EarFS* experiences the lowest accuracy drop (Δ= -4.8%) and does not perform significantly worse. Although CS and EFS significantly dropped in accuracy, we have to dismiss this hypothesis, because EMG did not significantly decrease.

Summary

The second study shows *EarFS* to not experience a substantial performance drop in mobility while the user is walking. Moreover, the study reveals that EMG is also not heavily affected by walking artifacts due to the nature of its' sensing method. Therefore, the study indicates that electrical field sensing related technologies may not be the perfect choice for a wearable gesture recognition, unless one applies a differential amplification, such as proposed in *EarFS*.

DISCUSSION

Considering the rather rudimentary electrode setup and the low-cost sensing device, in our opinion, the achieved classification accuracy above 90% with a gesture set of five is astonishing. This is due to the heterogeneous signal, which is a combination of facial-movement-induced ear canal deformations and biopotential processes. Still, a custom six channel *monopolar* EMG, using surface electrodes similar to Zhang et al. [40] but distributed over the entire face, tends to outperform any in-ear setups. We confirmed this in a pilot study where we attached 7 silver/silver chloride gel electrodes to the face in places right above facial muscles of interest (*see Figure 11*).

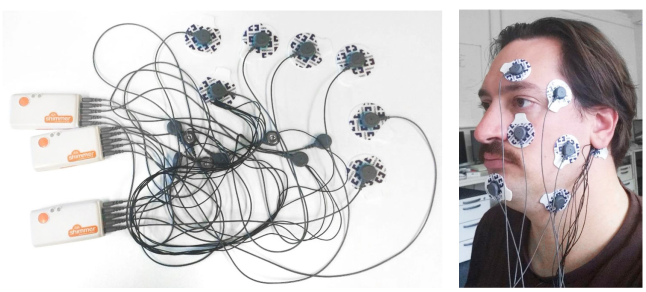

Figure 11. We utilized 3 Shimmer3 EXG sensor devices with 7 Ag/AgCl gel electrodes (6 channels + 1 common ground placed behind the ear, an area that remains relatively unaffected by muscular movement) to detect same gesture set.

We again recorded the complete facial gesture set of 25 with a sampling rate of 200Hz and a window size of 256. A total of 346 features (based on 46 state-of-the-art features) have been extracted from the raw data, whereby the most meaningful features included: *maxAmpFrequency*, *spectralEntropy*, and *logLikelihood*. With this setup, a *RandomForest* classifier performed best while detecting 25 facial gestures with an accuracy of 62%. A reduced set of only 5 facial gestures scored maximum accuracy of 100%.

This pilot clearly highlights the typical trade-off between technology that is obtrusive on the one hand, but on the other hand achieves high accuracy rates. Scoring comparably low precision with an in-ear setup is not surprising, since (1) the maximum number of channels tested with the earplugs was four and (2) sensors cannot directly sense evoking action potentials from the source while resting inside the ear canal. Nevertheless, we expect *EarFS* to technically mature with further iterations (testing different building blocks, EM shielding). However, placing more electrodes inside the ear is not expected to provide significant performance boosts. Instead, a combination of different technologies seems promising and is highly encouraged for further research. While electrodes with direct skin contact could be combined with electrically insulated electrodes, it did not increase performance in our study. In contrast, a future improvement would be to additionally determine the deformations of the ear canal with pressure-activated distance sensors. Another method would be laser-based distance measurements by using modulated laser beams and image-based phase-shift analysis in order to get a distance-to-skin measurement inside the ear canal. Particularly, laser modulation frequencies would have to be very high to cover the sub-millimetre distance range in this approach, and thus suitable hardware would increase the costs of such a sensing device.

CONCLUSION

In this paper, we presented a novel variant of an electrical field sensing (*EarFS*) which provides *hands-free* and partly *eyes-free* interaction for mobile and wearable computing. We introduced our developed sensing circuit in detail so that it can be replicated by any HCI researcher or practitioner. With *EarFS*, we closed an open gap in research while we systematically investigated detecting various facial-related gestures via an electric field sensing inside the ear canal, which has not been done before in this manner. We provided two studies that reveal how electric sensing technologies could possibly perform when using an electrode in-ear plug. On top of that, we were able to show that *EarFS* tends to outperform other electrical sensing approaches when it comes to facial-gesture recognition in mobility while the user is on the go.

FUTURE WORK

Since facial gestures and expressions cannot typically be 'switched off' by users, the field of mobile facial expression recognition still yields great potential as far as implicit interaction is concerned. Based on facial expressions, a future system would be able to know and anticipate the user's intentions before conscious interaction becomes necessary. In terms of apparatus, we believe that in-ear devices, such as earbuds, are much more unobtrusive and socially acceptable than other known hands-free and eyes-free technologies. Therefore, we envision similar sensing approaches to be integrated into in-ear headsets in the near future. Besides headsets, we also see great potential in *EarFS* to be implemented into various other kinds of wearables, since our sensing approach offers a much wider range of recognition capabilities for gestures and activities in mobility than discussed in this paper. Exploring these capabilities in future research could be very beneficial.

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