CapGlasses: Untethered Capacitive Sensing with Smart Glasses

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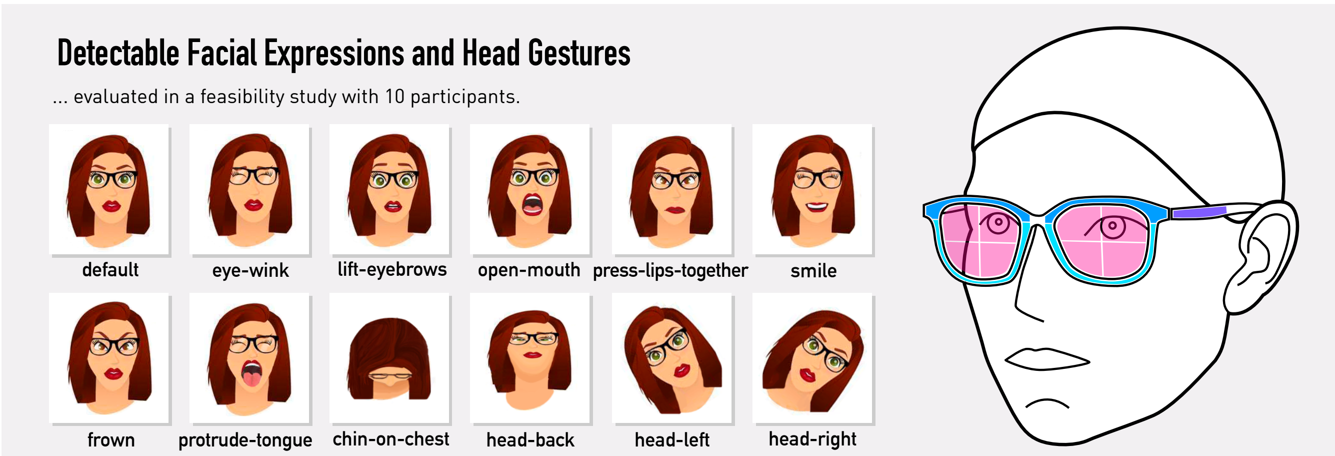

Figure 1: We present CapGlasses, an untethered capacitive sensing smart glasses prototype that is fully battery-powered. In a feasibility study we evaluated the detection of 12 different facial expressions and head gestures. Our lab study showed reasonable accuracy at 89.6% with a user-dependent model suggesting our CapSense design being applicable in mobile context.

ABSTRACT

Augmenting the human body using wearable technology can be particularly interesting to sense context. The user's context includes the mental and physical state, which is inferable by detecting facial and head related gestures. For the recognition of these gestures, we propose instrumenting a pair of glasses with Capacitive Sensing (CapSense) technology. We demonstrate proximity sensing with CapSense for mobile use despite its commonly known limitations in context of mobility. Moreover, we demonstrate how to incorporate transparent sensing electrodes into the glass and copper electrodes into the frame while being potentially invisible in a future specs product. We demonstrate an untethered battery-powered glasses prototype, CapGlasses, to sense facial expressions and head gestures. We selected a set of 12 gestures and ran a study with 12 users. We obtained an average accuracy of 89.6% by a user-dependent machine learning model. We focused on providing clear documentation to enable a straightforward replication of our technology.

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CCS CONCEPTS

• **Human-centered computing** → **Interaction devices**; **Ubiquitous and mobile computing systems and tools**; **Ubiquitous and mobile devices**.

KEYWORDS

Capacitive Sensing, CapSense, Electric Field Sensing, Body Potential Sensing, Facial Expression Control, Smart Glasses, Prototyping, Wearable Computing, Activity Recognition, Machine Learning, Data Mining

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1 INTRODUCTION

Facial expressions naturally occur and currently exist as grounds for research in the area of affective computing [41]. A pioneer in this area, Paul Ekman, established a facial action coding system (FACS) [13], which remains the ground-truth database for all facial movements and their associated emotional states. As we can utilize facial expressions for affective computing, we can then utilize them to infer on context information. For instance, implementing an implicit interaction [49] to adjust a system's behaviour based on the user's mental and physical state would be beneficial in a mobile driving task. Additionally, we could employ facial and head gestures for an explicit control enabling quickly executable Microinteractions [3]. As short natural gestures do not overtax the user's attention, they enable for Peripheral Interaction [4]. Moreover, a hands-free and parallel execution, which does not interrupt the primary task, can potentially enable for Reflexive Interaction [37].

The detection of facial expressions and head gestures remains the focus of current research, being of particular interest for collaborative Mixed Reality applications [38]. Circumventing the problem of expensive classification algorithms, recently, Facebook-Research [52] demonstrated a complex facial-gesture-mapping to a virtual avatar using a GAN Deep-Learning approach based on 9 cameras attached to a VR-HMD. However, for gesture recognition, literature has demonstrated the potential of utilizing other cost-effective technological solutions, such as Capacitive Sensing (CapSense) [42, 43]. A 'face-hugging device' [43], nevertheless, is too obtrusive to be socially acceptable. The first mobile approach was demonstrated in 2017 in EarFieldSensing [36], using a simple earplug, enabling the recognition of 5 gestures with reasonable accuracy of 90%. Other mobile wearable CapSense approaches that in particular utilize a proximity sensing have not been explored widely, as CapSense usually requires a mains ground for this. Literature has yet to demonstrate a technical solution that fulfils all requirements of being computationally inexpensive, socially unobtrusive, applicable in a mobile context, providing high accuracy for a reasonable number of gestures. We believe an ordinary pair of glasses utilizing CapSense technology can fulfil all four requirements.

Following Wobbrock [56], this research is an artifact contribution at which we demonstrate a wearable solution to sense facial expressions and head gestures by untethered CapSense technology. Previous wearable CapSense solutions were either tethered to mass/grounds, or prone to interference, or demonstrated low accuracy, or drove a current through the body.

2 RELATED WORK

According to Grosse-Puppendahl et al. [17], Capacitive Sensing (CapSense) can be seen as a broad synonym for any Electric Field Sensing. However, in this paper, we understand it as a sensing technique, in which at least one electrode is actively being charged. We organized previous work into two subsections, introducing general CapSense approaches and Facial Gesture Recognition in another subsection.

2.1 Capacitive Sensing

CapSense is not a novel technology, already being implemented within the last century into everyday objects, such as desk lamps. In research, several CapSense toolkits exist to enable researchers and designers to utilize Capsense beyond a simple binary switch, such as a proximity sensor. Likely, the most popular toolkit is Paul Badger's CapSense library[1], a software implementation utilizing an Arduino for measurements. Other important developments in HCI research include CapToolKit [55] and OpenCapSense [16]. Professional CapSense toolkits are also available on the market with a recent one being the FDC2214 from Texas Instruments[2]. CapSense is also embedded into many technological products, such as the screen of a smartphone, enabling the sensing of touch input, as well as pressure [10]. CapSense demonstrates a variety of versatile uses; it can identify a user by its gait through capacitive insoles [35], by pressing the user's unique ear against the capacitive touch screen [22], or by touching the screen with a capacitive ring, as Vu et al. [51] demonstrates. Using CapSense as wearable technology, such as in the shape of a ring [53], is powerful yet technically challenging, being quickly affected by environmental noise. Embedding CapSense into clothes, such as pants, jackets or shoes enables for precise recognition of walking activities [20], body postures, and the identification of the user's context, such as the floor the user walks on [35]. Using two wristbands, hand and finger postures can be identified [48]. In a stationary setup, one can enhance objects, such as a sofa [18] and a chair [7] with posture detection or enable for in-air gesture recognition by integrating CapSense into the frame of a screen [54] or a table [8]. In general, with CapSense, a great variety of conductive parts, such as metal objects, can be enhanced. Touché [48] demonstrates this, for instance, a smart doorknob allows for secret "password grasping gestures". Aside from these examples, many other CapSense instrumentations exist. However, research on capacitive facial gesture recognition is very marginal and mainly driven by Rantanen et al. [43], who developed a rather obtrusive "face-hugging device," requiring 12 electrodes that enable the sensing of four facial gestures with an average accuracy of 88-93%. In contrast, our goal is to use a less obtrusive hardware setup while achieving similar or better recognition rates.

2.2 Facial Gesture Recognition

Facial gestures can be sufficiently detected using visual approaches, such as camera tracking [5]. This has been extensively used in the area of affective computing [14]. Recently, Facebook Research presented a complex facial expression mapping to a virtual avatar using a GAN Deep-Learning approach by relying in 9 IR-Cameras attached to a VR-HMD [52]. Technically speaking, their approach is not a gesture recognition as it is also computationally expensive and immobile. In a mobile context, when the user is walking, it is unusual to have a camera positioned in front of the user's face. Even wearable micro-cameras have the drawback of being heavily impacted by light conditions. Therefore, other wearable technologies come into play. Some mobile facial gesture control prototypes utilizing different technologies have been developed and tested in the past, although their spectrum of recognition was rudimentary. San Agustin et al. [46] demonstrated the detection of a frown or the tightening of the user's jaw while using an EMG headband. By EMG one is sensing electric activity generated between two opposing electrodes. A similar setup with more electrodes was proposed by Chen et al. [11] demonstrating to discriminate between 5 facial expressions by a neuronal network approach with relatively high accuracy of 97.12%. Another headband that can distinguish 'raising eyebrows' and 'lowering eyebrows' from the default state deploys force sensitive resistors (FSR) [59]. A rather unobtrusive wearable device that attaches EMG electrodes to the temple region was proposed by Gruebler & Suzuki [19] enabling to distinguish 'smiling',

[1]Paul Badger's CapSense Library: *http://playground.arduino.cc/Main/CapacitiveSensor*

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

Table 1: Comparison of CapGlasses to the state-of-the-art in research that demonstrates the detection of facial expressions and head gestures. The number of gestures shown excludes the default (resting) gesture.

Name	Venue 'Year	Technology	Location	$n_{Gestures}$	Accuracy	Dependency	Classifier
Saponas et al. [47]	UIST '09	Infrared Sensing	in mouth	4	90%	cross-user	DT
Rantanen et al. [43]	IEEE Sensors '13	Capacitive Sensing	on face	4	88% - 93%	cross-user	LR
Ishimaru et al. [25]	AH '14	Infrared Sensing	face (glasses)	1	93%	per-user	DT
Zhang et al. [57]	CHI '14	Electromyography	on throat	5	94.17%	per-user	SVM
Gruebler & Suzuki [19]	IEEE TAC '14	Electromyography	on temple	2	95%	per-user	NN
Kanoh et al. [27]	EMBC '15	EOG	face (glasses)	1	94.3%	cross-user	n/a
Chen et al. [11]	Neurocomputing '15	Electromyography	face (headband)	4	97.12%	per-user	NN
AffectiveWear [31]	ISWC '15	Photo LEDs	face (glasses)	6	98.7%	per-user	SVM
Bitey [2]	MobileHCI '16	Bone-Conduction Mic.	back of head	5	78%	per-user	SVM
EarFieldSensing [36]	CHI '17	Electrical Field Sensing	in ear	5	90%	per-user	DT
CanalSense [1]	UIST '17	Barometer	in ear	10	87.6%	per-user	RF
W!NCE [44]	IMWUT '19	EOG + IMU	face (glasses)	4	88%	per-user	CNN
Interferi [24]	CHI '19	Acoustic Interferometry	on face	8	89%	per-user	RF
ChewIt [15]	CHI '19	Accelerometer + Button	in mouth	9	86.1%	per-user	DT
KissGlass [28]	AHs '20	EOG + IMU	face (glasses)	3 (10)	74.33%	cross-user	kNN
Masai et al. [30]	AHs '20	Photo-reflective Sensors	face (glasses)	7	89.1%	per-user	SVM
Expressure [59]	MDPI Sensors '20	Force Sensitive Resistors	face (headband)	2	82.4%	cross-user	SVM
CapGlasses	AHs '21	Capacitive Sensing	face (glasses)	11	89.6%	per-user	RF

'frowning', and a 'neutral expression'. In 2012, Matthies et al. [33] used an EEG headset to detect eye winks and head movements. The EEG working principle is similar, although it utilizes greater amplification. Later, an in-ear prototype [32] was proposed that detects ear wiggling and eye winks. Recently, a further development of an ear plug [36] reliably distinguishes five facial expressions ('eye wink', 'head right', 'open mouth', 'say SH', 'smile'). Other approaches are rather obtrusive, such as gluing a magnet to one's tongue [45] or applying EMG electrodes directly onto the user's face [57]. In 2018, Inzelberg et al. [23] proposed to attach EMG electrodes onto the cheeks in form of some kind of skin tattoo. In the same year, Li and Reyes [29] demonstrates attaching five infrared proximity sensors to VR goggles to infer on the continuous lip and jaw motions by measuring deformations of the cheeks and temples. Another VR HMD by Bernal et al. [6] enables the classification of a variety of emotional states using EMG, EOG, EDA, and EEG sensors. Nine facial gestures are detectable with a bio-acoustic sensing [24], applying a rather obtrusive sensing layer onto the face. A less unobtrusive form factor would be a pair of glasses. Ishimaru et al. [25] demonstrate a blink detection based on the infrared proximity sensor of Google Glass. Bulling et al. [9] developed EOG Glasses with six electrodes that allow for the tracking of eye movements. In EOG we detect the voltage difference between two opposing electrodes. Moreover, Masai et al. [31] attached eight photo reflective sensors to a glasses frame, which detected 'smile', 'laugh', 'disgust', 'angry', 'sad' and a 'surprise' gesture. For photo reflective sensing, one usually uses an emitting LED plus optical sensing diods. Kanoh et al. [27] and Rostaminia et al. [44] use a commercial EOG glasses (J!NS MEME) to classify facial expressions. Only Rantanen et al. [42] present a pair of glasses using CapSense. Typicalley an electrode is charged in a certain frequency as the charging time can infer on the generated capacitance. Rantanen et al. [42] is capable of detecting a 'frowning' and a 'lifting of eyebrows' to execute click-events with an average accuracy of 82.5%, but which leaves space for improvement in terms of the variety of detected gestures.

An overview of significant related work is also summarized in Table 1. The table also illustrates how CapGlasses is positioned towards the state-of-the-art in terms of gesture recognition properties. In contrast to previous works, CapGlasses is capable in detecting 12 (11 + 1 default) gestures with a reasonable high accuracy. While the same type of gestures can be recognized with other prototypes, one must acknowledge that each technology has its (dis-/)advantage and use case. For instance, camera fails with bad light, IMU barely works when walking or in a car, mouth-placed sensors might not be acceptable, etc. Another aspect worth looking at is the model's dependency. Since the face in particular has a very individual form and expression, in previous research, models for machine learning were trained that are mainly personalized (per-user) and not generalizable (cross-user). Cross-user models seem to only support a limited number of gestures.

3 CAPGLASSES

As far as facial expression recognition is concerned, Capacitive Sensing (CapSense) can be useful for proximity sensing. Particularly, Rantanen et al. [43] already demonstrated how to use capacitive sensors in a loading mode to detect facial activity with a face-hugging prototype. While their prototype is capable of detecting 4 facial expressions, it is still bulky and obtrusive. Our goal is it to find out whether we can achieve higher recognition rates with an even more unobtrusive prototype, such as in the setup of a glasses frame. In the following subsections, we briefly introduce how CapSense works and what kind of benefits are potentially enabled when employing this technology within a pair of glasses.

3.1 Background of Capacitive Sensing

Capacitance generally describes the amount of electrical charge that can be stored between different objects, relative to each other.

It is not limited to the standard electrical component 'capacitor', but can be asserted between any two (or more) charge-carrying objects. Capacitances of this kind can be introduced by asserting virtual capacitors – any two arbitrary objects form a capacitor. In our everyday environments electrical charges are ubiquitous, which explains the widespread use of capacitive sensing technology in many different applications. Interestingly, apart from everyday objects, the human body also carries charge. Capacitances are thus all around us. In a standard CapSense loading mode, the capacitance between a single measuring electrode and its surroundings is determined by measuring how much electrical charge the electrode can store. Since it is hard to directly measure the amount of charge the electrode can store in loading mode sensing, the time it takes for the electrode to reach a predefined voltage level is repeatedly measured instead. It is important to note, however, the object to be detected determines the performance of a capacitive measurement, as well as the use case, which informs the size of the electrode.

3.2 Benefits of Capacitive Sensing Glasses

A CapSense glass frame has the advantage of being highly inconspicuous, unobtrusive, and socially accepted. With the advent of transparent capacitive sheeting – as known from smartphone screens – a measurement electrode array can be implemented that allows for high facial-spatial resolution in a small form-factor. Electrodes can be incorporated into glass frames or even eyeglass lenses at low costs. Novel electrodes based on enhanced silicon-rubber (e.g. mixed-in graphite, silver- compounds) or Indium Tin Oxide can even be completely invisible. The ability to accurately measure facial gestures offers great potential for implicit interactions. Facial gestures virtually never consciously switch off and thus exist as a reliable source of information. Time-series facial data analysis can infer stress levels, arousal, or exhaustion. Even for a sleep-analysis, an eye-mask could easily be fitted with flexible electrodes and deployed while preserving comfort. In terms of recognition, our approach works well because our unique technology allows us to leverage on: (1) the physical arrangement of the electrodes that cover a relatively large area in front of the face and (2) sensing both, contact with the electrode and proximity changes, which reflects deformation and movement of the skin during a gesture.

3.3 Challenges of Capacitive Sensing

Although CapSense enables for great sensing capabilities, it yields challenges. Typically, a capacitive sensor is supposed to sense activities in a certain direction. For instance, an antenna could be a sensing electrode attached to a glasses frame and facing the user's face aiming to record facial activity. However, the antenna is omnidirectional. In result, the antenna picks up any environmental change, such as movements or electrostatic changes in the near vicinity. We can minimize the effect by shielding the backside of the antenna with another electrode (either grounding it or using the same potential), but which can also result in a decreased overall signal range. Moreover, we can perceive that absolute sensor-readings might slightly change throughout the day based on a great variety of environmental interference. To counter this, we can make use of signal processing techniques, such as using a detrend filter, normalization etc. To end up with a stable signal we can further reduce the signal range, but that is not very desirable for proximity sensing. Another issue is signal saturation, such as when the dielectric is insufficiently great in size. This can quickly occur when the electrode gets in contact with skin. However, the pressure and the size of the area of the skin touching the electrode can still create unique signal patterns. For instance, a big smile would touch the electrodes of the glasses frame in a different way than when frowning. Finally the electrical mass/ground capacitance the sensing circuit is connected to determines the signal quality and signal range. For instance, a 155mAh battery would result in very low (signal-to-noise ratio) SNR in comparison when plugging the sensing circuit to a stationary power supply. This limits CapSense for an actual mobile use, when the user would walk around freely.

3.4 Untethered Mobile CapSense Solution

Within the scope of this research, it was our interest to investigate a hardware configuration that can be truly mobile without being tethered to an external ground and thus would be hardware-wise self-contained. Once the capacitive sensing circuit is no longer tethered to a stationary ground source, the sensitivity and signal-to-noise ratio is substantially reduced making it hard to sense changes invoked by facial expressions and head gestures. This is because the capacitive coupling between the body and the electrodes becomes so low that it gets lost in noisy sensor readings. Instead all other types of EM-waves predominantly override the signal.

To overcome this, we investigated two different strategies enabling us to receive meaningful sensor readings:

- *Opt. A*: Amplifying the signal changes by the body. This can be done by elevating the body's potential, such as through injecting a 12V AC. This would create a dominant change in the sensor readings.
- *Opt. B*: Generating a sufficiently great electric field close to the face and close to the electrodes, capable of impact from changes through different facial and head gestures.

Although we attempted both options, we decided to pursue *Option B*, as driving an electrical current through the skin might have some negative, yet unexplored, long-term health effects. Also, literature has somewhat demonstrated *Option A*, for example, in OmniTouch [21] and SkinTrack [58].

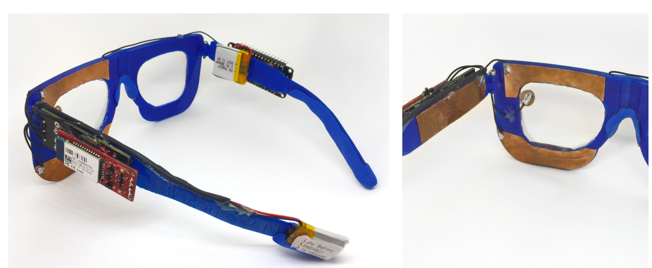

Figure 2: The frame is 3D printed as we attached blue modelling foam to it in order to improve wearing comfort. One of the four sensing electrodes is a conductive glass coated with an Indium Tin Oxide (ITE) layer.

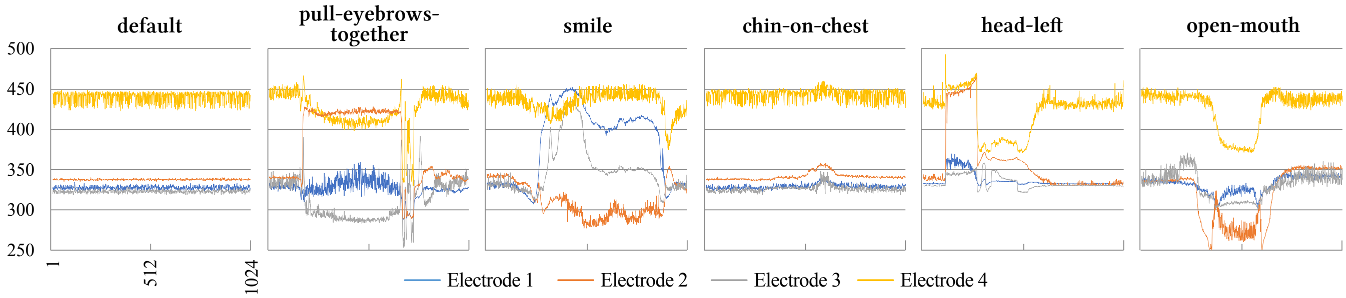

Figure 3: Displaying the raw data signals of six randomly selected gestures from a random user.

4 IMPLEMENTATION

4.1 Apparatus

We 3D-printed a modified model of an existing 3D specs model. We enlarged the frame to maximize the surface area where we can attach electrodes. The prototype was printed using a Fused Deposition Modeling (FDM) printer. As the prototype is heavier than an of-the-shelf pair of specs, we attached some soft modelling clay to the frame that touches the skin for increased comfort. We deployed four sensing electrodes to one of the sides (*see Figure 2*). Moreover, we attached a single electrode to the exterior of the glasses frame to generate a small electric field (*see Figure 4*).

4.1.1 Field Generation: To generate an electric field, we use a resonant tank consisting of a 110pF capacitor and a 1mH inductor, resulting in a resonant frequency around 480kHz. By feeding it with a square wave from a microcontroller, we are able to generate an AC voltage of around 80V p-p. This consumes ∼20mA and would last for ∼19h with our 380mAh battery. Due to practical reasons, we decided to place the electrode emitting the electric field opposite the sensing electrodes placed on the outside of the glasses' front frame (*see Figure 4*). However, other variations, such as putting it to the side are also feasible. Please note, this electric field carries a very low load of energy. Even accidental touches would result in a voltage drop to ∼1V as the frequency changes due to the body's resistance.

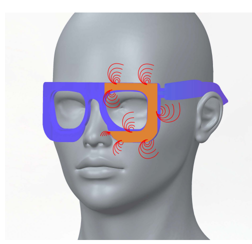

Figure 4: A large surface electrode attached to the front frame generates an electric field surrounding it. The red lines illustrate some electric field lines. Apparently, the electric field has a greater range (not shown in this limited illustration), however, the amplitude strength quickly decreases. With our sensing technology we could sense changes within a radius of ∼5cm.

4.1.2 Sensing: This setup uses an altered version of the EarFS [36] sensing circuit. The second AMP (U1) is no longer required. Also, we bridged C1 to bypass the high pass filter and removed C3 to receive a wider spectrum of high frequencies. Further, we opened the INA's gain by setting R1 to almost 0 Ohm – we used a potentiometer for flexibility. As the signal is strong enough to override ambient noise and artifacts created from other body movements, such as walking, we do not need to attach a reference electrode. Moreover, we eliminated flying wires and integrated all electronics into a custom SMD PCB. To increase clarification and to enable a straight forward replication, we attached the schematics to the appendix. Our custom board incorporates an Arduino (Microcontroller: Atmel ATSAMD 21G18A). We use an RN42 Bluetooth 2.1 modem to stream the sensor data in bursts to a computer storing the data by a Java application. The entire prototype is powered by a 155mAh LiPo battery and consumes ~60mA, which grants us a lifetime of ~2.5h.

4.1.3 Performance: As we generate a stable EM-field, the sensing is not greatly irritated by taking off and putting on the glasses. Our circuit is tweaked to be invariant to typical EM noise that surrounds us. However, very close fields, such as wearing a big headset, can cause interference. During the design of the prototype, we faced the trade-off between the number of electrodes vs. large electrodes. Apparently, a higher number of electrodes create a greater resolution, however, since we are limited in space that the glasses offer, we require to decrease the size of electrodes at the same time, which results in a weaker signal. After long testing, we optimized our setup for electrodes with 3-10 cm^2. Throughout pilot studies, we did not see significant performance differences in covering both sides with electrodes as gestures are mainly symmetrical.

4.2 Study Design

To check the performance level, we invited 10 participants from various backgrounds (2x Germans, 3x Sri Lankans, 2x Chinese, 1x Singaporean, 1x Iranian, 1x Indian), aged between 21 and 36 years (M = 29; SD = 4.6) and recorded their facial and head gestures. None of the participants was familiar with a study of this type. All users voluntarily participated and consented to provide their data. We recorded a gesture set containing the following 12 gestures:

> *(a) chin-on-chest, (b) default, (c) eye-wink, (d) head-back, (e) head-left, (f) head-right, (g) lift-eyebrows, (h) open-mouth, (i) press-lips-together, (j) protrude-tongue, (k) pull-eyebrows-together, and (l) smile.*

The study leader triggered the gesture recording after orally commanding the participant to start execution. With 500Hz, sensor data fills a 1024 array giving each gesture space of 2s. Each gesture is picked up by four sensing electrodes. The participant was asked to repeat each gesture 10 times. We did not pre-process the data and calculated 46 state-of-the-art statistical and frequency-based features commonly used in literature over the entire window of 1024 samples. This approach is part of a conventional machine learning pipeline that we followed. We were unable to not successfully perform a leave-one-user-out cross-validation, because our data is user-dependent since individual factors are strongly pronounced *(see discussion)*. Therefore, for each user, we built an independent model, taking into consideration the individual physiology of users' faces as well as the execution style of gestures that also differed greatly across users.

4.3 Results

To build our machine learning model, we selected a *RandomForest (RF)*, as our previous studies determined this to be a suitable classifier for our data. The RF auto-selects meaningful features, which were: *Median, geometricMean, minElement, maxElement, pairDifference, Variance,* and *signalIntensity*. We can see that statistical features are predominant, also indicating no unwanted high-frequency EM-noise impacting our data. *Figure 3* depicts the raw signals during gesture execution. As popular among related research, we ran a 10-fold cross-validation, training the model with 9 instances and testing against the remaining one and iterating this 10 times. The average accuracy across all users showed a true-positive recognition of 89.6% (*mean F1*=.8956, σ=.0605). A confusion matrix, accumulated and averaged across all users, is depicted in Figure 5.

a	b	c	d	e	f	g	h	i	j	k	l	<
92	1	2	0	0	0	3	1	1	0	0	0	a
1	95	1	0	0	0	1	0	0	0	1	1	b
2	3	90	2	0	0	1	0	0	0	1	1	c
0	0	0	95	0	1	1	0	1	1	1	0	d
0	0	0	1	93	4	1	0	0	0	1	0	e
0	0	0	1	2	94	1	0	0	2	0	0	f
2	0	1	0	0	3	86	2	0	2	3	1	g
0	0	1	0	1	0	5	84	2	2	3	2	h
1	0	0	1	0	0	3	5	84	2	1	3	i
1	0	1	1	0	1	4	3	1	84	0	4	j
1	1	0	1	0	2	0	2	1	0	92	0	k
0	1	0	0	0	1	0	5	4	2	1	86	l

Figure 5: Confusion Matrix showing true-positive rates and confusions [in %] using a *Random Forest* (Average accuracy: 89.6%). The top 5 gestures (next to the default gesture) include: d) head-back, f) head-right, e) head-left, a) chin-on-chest, and k) pull-eyebrows-together.

It became obvious that most confusions occurred around the cluster of (h) open-mouth, (i) press-lips-together, and (j) protrude-tongue. A more reliable recognition than these facial expressions are gestures that involve greater head movements, such as d) head-back, f) head-right, and e) head-left. This is because head movements invoke higher motion changes than facial expressions.

4.4 Discussion

4.4.1 Fine-tuning. Based on our experiments, a fine-tuning of the sensing apparatus can provide higher accuracy for low-amplitude movements as well. However, high-amplitude motion stemming from head movements might not be distinguishable anymore, as the signal would become saturated. A solution would be instrumenting both sides of the glasses with two different configurations. One would be as fine-grained to pick up eye-blinks and the other would only pick up head movements.

4.4.2 Individual Physiology. Besides the individual gesture execution style, we also observed that the physiology of the participants' faces have a major impact on the accuracy. For instance, participants demonstrating a rather flat face and small noses, which is common amongst the Asian population, show better recognition results. This is because the face is closer to the electrodes, meaning they are touched more often when executing certain gestures, resulting in more distinct signatures. In fact, the bottom electrode constantly touches the cheek, which also contributes to a totally different gesture pattern making generalizability across other individuals impossible. Training a successful model based on a single user seems only to make sense when users have a matching face shape and commonalities in gesture execution. A brief test between two Sri Lankan participants showed a match of ~25% accuracy among all 12 gestures and ~70% with 5 gestures.

4.4.3 Mobile Feasibility. During our exploration, we recognized that using a second electrode generating an electrical field behind the sensing electrode seems to provide more stable results than previous capacitive sensing methods. Also, it was possible to walk around without receiving great interference from other electrical devices or artifacts from body movements. We believe this setup, which is similar but not exactly like a shunt mode, to be very promising for future research in mobile and wearable computing.

5 CONTRIBUTIONS, BENEFITS, & LIMITATIONS

We and other researchers, such as Ekman and Friesen [13], see facial gestures as providing a valuable source of information. Merely using an ordinary pair of glasses can sense hidden information. Previous advantages demonstrated in scientific literature, as well in recent products, have shown that smart glasses are becoming more important in wearable computing. In this section, we elaborate how this paper contributes to the state-of-the-art, as we summarize the resulting advantages and limitations of CapGlasses.

5.1 Contributions

In this paper, we explored a way of integrating capacitive sensing for glasses and in a truly mobile manner, without requiring the need to drive an electric voltage through the body. Although most works can solely focus on exploring technology, others have a stronger focus on creating social-acceptable solutions, or investigating the applicability in truly mobile scenarios (in which users are walking and interacting). With CapGlasses, our main focus is twofold; we explored proximity sensing with CapSense for mobile use and we explored how CapSense can be incorporated in a glasses frame, which can be more unobtrusively hidden in a future specs product.

Figure 6: Beneficial Use Cases: a) Very recently, BMW introduced its Intelligent Person Assistant [40], an assistive intelligence that supports the driver in various ways, such as enabling a relaxation mode when the driver states to be stressed. Based on facial expressions, a pair of smart glasses could automatically detect stress and when the driver is tired. Utilizing these information can improve automated assistance and driving experience. b) The Wall Street Journal recently showed how China is using Artificial Intelligence in classrooms [26] while pupils are equipped with head-worn EEG devices that measure concentration and engagement. Using smart glasses to infers on task engagement based on facial expressions could be an alternative solution being more inconspicuous. c) Back in 2011, Microsoft proposed the use of smart glasses in their Productivity Future Vision [39]. Here explicit facial expressions, such as an eye wink or a head movement could be used to interact with the device enabling hands-free interaction and benefiting efficient multitasking.

5.2 Benefits

5.2.1 Glasses Form Factor. We consider utilizing a pair of glasses to measure facial expressions and head gestures as an elegant solution. Because a pair of glasses is not an additional sensing device and already worn by many users, it allows for the subtle implementation of sensing technology. Since the frame and the glass itself offers large surface area, we can implement area electrodes, which are sensitive enough to sense any facial and head movements. Similar to a capacitive touchscreen, we can also utilise transparent electrodes. Our prototype used Indium Tin Oxide electrodes, however, in mass manufacturing a vapor deposition of electrodes may be favoured. Moreover, these electrodes could be further separated to increase resolution, as highlighted in *Figure 1*. Smaller surface electrodes, however, will minimise sensing distance.

5.2.2 The Power of Facial Expressions. Facial gestures are ubiquitous in everyday interactions. In mobile and everyday contexts, an unobtrusive pair of glasses can not only provide safety benefits by allowing the user to reflect on their current state, such as the level of tiredness, as recently showcased by Tag et al. [50], but aid in several other ways. Moreover, dangerous situations are often characterized by pronounced facial gestures. Facial gestures are useful in reflecting emotion, such as shock for example. Also, facial data analysis can infer a user's engagement in a task. In the future, sensing facial gestures can enable enriched implicit interactions, as well as explicit interactions, while tapping into vast reservoirs of data humans naturally produce.

5.2.3 Use Cases. Sensing the user's context is an essential aspect of future assistive technology [12]. Context information includes the mental and physical state, which can be inferred by facial expressions. For example, an assistive system could increasingly support the user when engaged in critical work tasks and activities, such as driving a car (*see Figure 6 - a*). Moreover, such a system can assess the user's unease or the difficulty experienced when performing a task (*see Figure 6 - b*). In a learning scenario, the difficulty could be individually regulated to adjust to the user's current performance level. In most clinical settings, tracking the mood and stress of a user is important. Currently, user's are often required to track such parameters at certain intervals manually. We envision a pair of glasses recognizing these facial gestures automating this process. At last, facial expressions and head gestures can be used to input explicit commands that are hands-free, thus safe to use when on the go, and enabling a more efficient multitasking (*see Figure 6 - c*).

5.3 Limitations

5.3.1 Unintentional Control. As facial gestures and head movements occur naturally, utilising them for explicit control may trigger significant false-positives. Context-aware interfaces must help here to understand the user and to offer appropriate interaction options at given times. Furthermore, training is required to utilise these gestures for quick responses to a system notification. However, if successfully internalised, CapGlasses could enable Reflexive Interaction [37], benefiting a reduced task interruption.

5.3.2 Reported Accuracy. Our prototype is unique in a way that it is untethered, which is prone to suffer from lower accuracy compared to CapSense tethered to an electrical mains ground. Still, with our special setup we achieved accuracy rates of 89.58% for 12 gestures utilizing four channels covering only one side of the face. However, we consider these rates as a theoretical accuracy level, reflecting the performance under "laboratory conditions". We would like to note that accuracy rates reported in this, as well as in the majority of other research papers, barely reflect those in reality when noise from causative (extrinsic & intrinsic), intermediate, and deterministic factors occur. Thus accuracy rates, including ours, can only be seen as a performance indicator. In practice, performance will look different and is very likely to drop. To increase robustness, we suggest a reduction of the gesture set to a lower number, using numerous training sessions and a self-learning classifier.

5.3.3 Environmental Influences. The most competing technology would be an optical sensing approach, such as demonstrated by Masai et al. [30]. However, environmental factors substantially influence the sensor data, so their prototype is only working when the user does not angle their head in a different direction as light conditions change. The feasibility in an actual mobile scenario is thus compromised. Our prototype is not impacted by these issues. However, it is also impacted by other environmental influences, namely where many electric devices emitting considerable EM-waves are within the vicinity. Also, we observed that wearing headphones has an impact on the sensor readings when using passive sensing. Moreover, the signal may slightly fluctuate from day-to-day, depending on a variety of factors, such as the user's electrical charge and neighbouring devices being switched on/off. Further, varying humidity and dryness of the skin could influence the readings. In particular, EOG, EMG, Bioaccustic, and Capacitive sensing is affected by the constant change of our body. A long-term evaluation of this effect in an interaction setting has been studied by Matthies et al. [34].

5.3.4 Signal Quality and Mobility. The size of the electrode and the extent of the electrical mass/ground capacitance of the power source impacts the signal quality significantly. For instance, a 550 mAh battery demonstrates a substantial lower SNR, as well as a decreased sensor range, compared to when it is plugged to a stationary power supply. However, when plugged to a stationary power supply, the mobility is apparently limit. To provide a truly mobile solution without being tethered to mains ground / earth, we suggest either enhancing the capacitive coupling between the body and the sensing electrodes, such as by increasing the body's potential (charging the skin with a low AC voltage), or creating a small electric field nearby the body and the electrode, such as shown by our prototype.

6 CONCLUSION

Facial and head gestures are a natural way in which humans represent emotions. Being able to record such gestures may contribute to a greater understanding of the human mental state, which could assist with rehabilitation or used to augment human and computer interactions. We were driven to search for a technical solution that fulfils the requirements of being computationally inexpensive, socially unobtrusive, applicable in a mobile context, and providing high accuracy for a reasonable number of gestures. With this motivation in mind, we developed CapGlasses a pair of CapSense glasses. To allow a straightforward replication of our prototype, we provide a detailed documentation.As electrodes can be easily manufactured into a pair of glasses, we believe our work will finally set an impetus for a novel way of recognising gestures with future smart glasses. Besides glasses our technology can be re-purposed for any other type of wearable, such as wristband, footwear, etc.

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APPENDIX

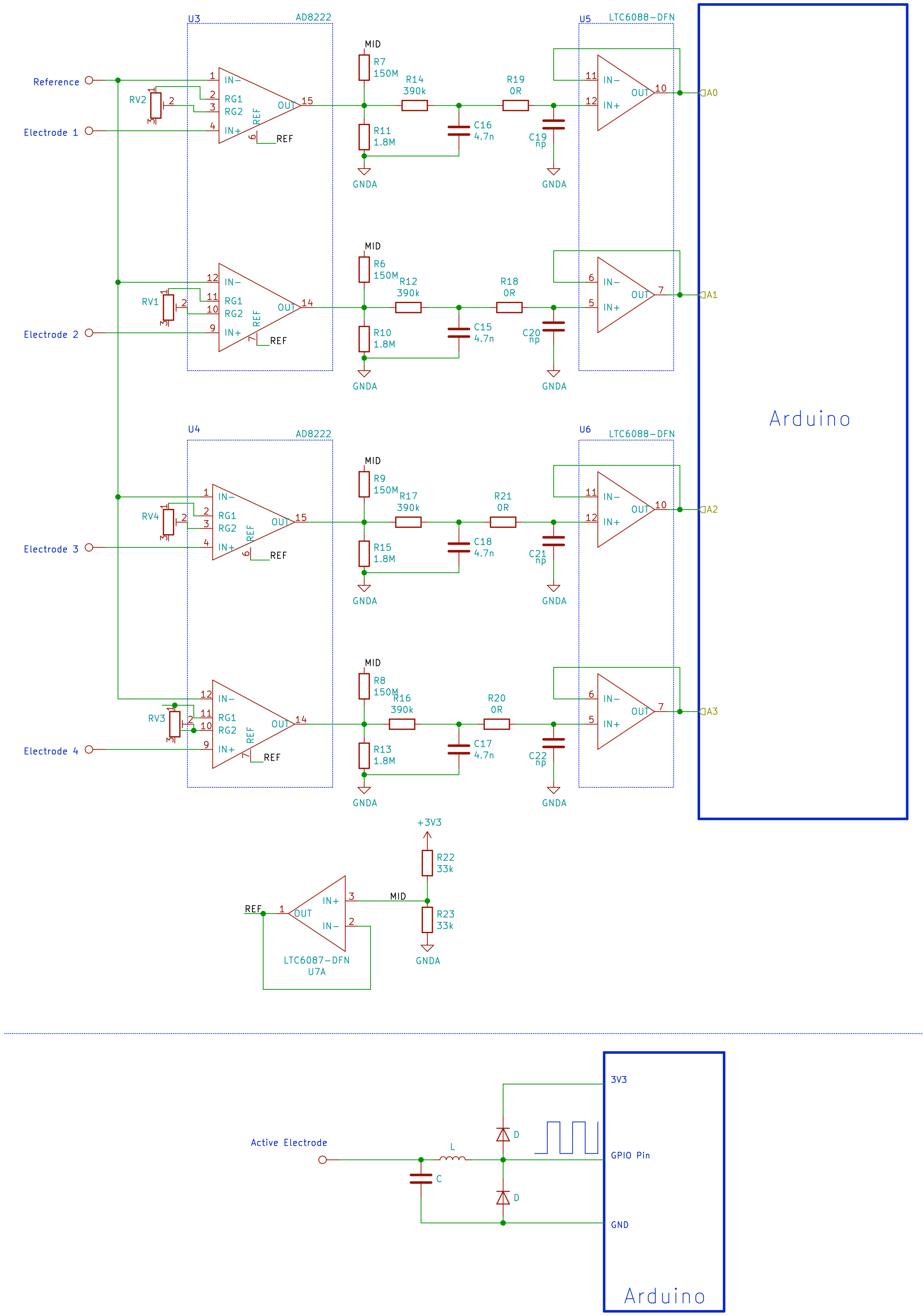

Figure 7: Simplified schematics of the sensing circuit (top) and signal emitting electrodes (bottom).