JINSense: Repurposing Electrooculography Sensors on Smart Glass for Midair Gesture and Context Sensing

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ABSTRACT

In this work, we explore a new sensing technique for smart eyewear equipped with Electrooculography (EOG) sensors. We repurpose the EOG sensors embedded in a JINS MEME smart eyewear, originally designed to detect eye movement, to detect midair hand gestures. We also explore the potential of sensing human proximity, rubbing action and to differentiate materials and objects using this sensor. This new found sensing capabilities enable a various types of novel input and interaction scenarios for such wearable eyewear device, whether it is worn on body or resting on a desk.

Figure 1: JINS MEME EOG electrodes placement on the nose pad and nose bridge. This placement makes the it non obvious and the device looks like a normal pair of glass.

CCS CONCEPTS

• **Human-centered computing** → **Gestural input**.

KEYWORDS

Smart eyewear, Electrooculography, Midair gesture, Context sensing

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1 INTRODUCTION

Wearable computing is becoming pervasive in our life with the proliferation of wearable devices such as smartwatches, fitness trackers, and smart eyewear. In particular, smart eyewear such as the Google Glass [5], JINS MEME [8–10], North Focals [13], Snap's Spectacles are becoming popular. It is also rumored that both Apple and Facebook are working on Augmented Reality (AR) glasses. These eyewear devices normally include various sensors, including inertial measurement unit (IMU), microphone and optionally camera(s) for sensing and tracking the context, environment and hand, under various real-world conditions. Some of these eyewears are also equipped with output capabilities such as display or speaker for immersive interaction in AR and VR environment.

However, due to privacy concern [4], people are wary of eyewear with obvious form factor, especially those equipped with camera(s), such as the Google Glass, Snap's Spectacles or Microsoft HoloLens. Therefore, there is another trend of smart eyewear with subtle design, where it looks like a pair or normal glass, yet it can still provide basic but useful functionality, such as the North Focals (minimal display for notification) or JINS MEME (no display).

For example, JINS MEME is a smart eyewear that looks just like a basic pair of glass [9, 10] (Figure 1). Yet, it has Electrooculography (EOG) electrodes that are built into the nose pad and nose bridge, which is not obvious at all. The EOG sensors on JINS MEME are used for sensing signal related to human eye, such as eye motion, eye movement [3, 15] and eye blink [16]. On a higher level, it can be also used for tracking alertness [17], cognitive and social interaction assessments [2], activity recognition [7, 19], fatigue [17], reading words [6], among the others.

Recent work shown that it is possible to repurpose the EOG sensors on the eyewear for facial action detection [14] and nose touching interaction [11]. These research inspire our work here. However, previous work are contact-based sensing where the electrodes touch the skin. Here, in JINSense, we try to achieve non-contact based sensing. In particular we are interested in (i) midair hand gesture sensing (ii) human proximity sensing and (iii) material differentiation.

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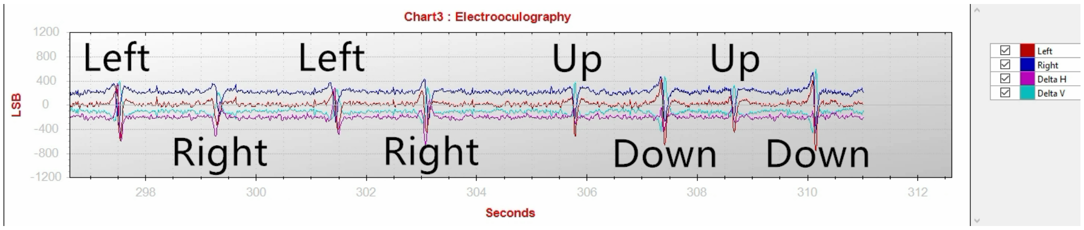

Figure 2: The raw EOG sensor signals show unique pattern when different hand gestures are performed. This figure shows the gesture left, right, up and down.

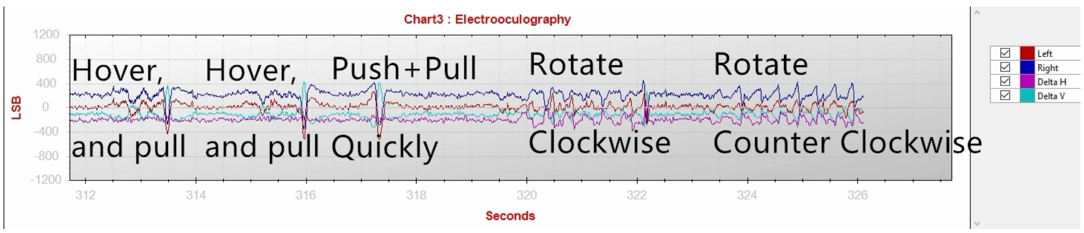

Figure 3: This figure shows the EOG signal for gesture hover and pull, push + pull quickly, rotate clockwise and counter-clockwise.

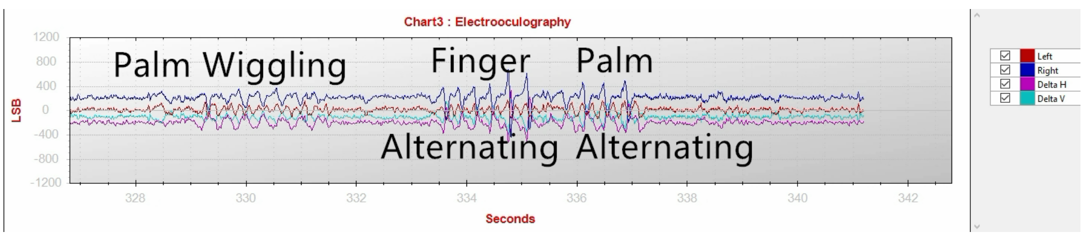

Figure 4: This figure shows the EOG signal for gesture palm wiggling, finger alternating up down and palm alternating up down.

2 RELATED WORK

In related work, midair gesture are typically detected using camera, microphone, capacitive sensor, infrared sensor or even radio frequency (e.g., radar sensor). To the best of our knowledge, EOG sensor has not been explored for midair gesture detection.

3 SENSOR BACKGROUND

Our eyes behave as dipoles with a constant electrical potential with the cornea acting as positive and the retina acting as the negative pole. The magnitude of this corneoretinal potential (CRP) is in the range of 0.4mV to 1.0mV [1]. If we move our eyes also the dipole and the electrical potential moves. This movement can be captured using electrodes taped around the eye (usually measuring the potential change left/right for horizontal and up/down for vertical movement). This procedure is called Electrooculogram.

In the JINS MEME hardware, there are three EOG electrodes, one placed on the nose bridge and one each placed on the left and right nose pad. We can measure potential V_L as the potential between electrodes left and bridge (Figure 1), and V_R as the potential between electrodes right and bridge [18]. Then we can calculate $V_{vertical} = -(V_L + V_R)/2$ as is the up-down eye movement and $V_{horizontal} = V_L - V_R$ as the side-to-side eye movement, assuming that eye balls move in the same direction.

Nonetheless, the equations above only apply to eye related signal when the device is worn as usual, where the EOG electrodes directly touch the user skin, and therefore the extracted raw data consists of mainly eye motion signal. However, when the user is not wearing the device, such as when being left on a desk or hang in the front pocket, the electrodes work in a way that is similar to electric field sensing. It senses the disturbance in electric potential difference in the surrounding air. These disturbances can be caused by hand gesturing nearby the sensor, or human body moving nearby the sensor. We can exploit this phenomenon and repurpose the sensor for sensing new modalities such as hand gesture detection, human proximity sensing and material differentiation. Example signals for these gestures are shown in Figure 2, 3 and 4. From these figures, we can observe the difference between signals of different gestures.

4 IMPLEMENTATION

To explore whether we can recognize midair gestures using this built-in EOG sensor on the JINS MEME device, we developed a prototype system that can collect, train, and classify different gestures from the signals. In this system, we stream raw data from the JINS MEME device over Bluetooth to a remote laptop for real-time signal processing and machine learning classification. We implemented the software in Python with libraries. In particular, we used Pygame for the user interface, SciPy for signal processing, and Scikit-learn for recognizing midair gestures with machine learning classifiers.

Initially, we took a simple approach using heuristic rules as a first attempt at achieving real-time gesture recognition without relying on machine learning. This approach calculates the peak and valley of the signal with predefined thresholds and classifies the gestures. However, the accuracy was far from usable, hence we proceed to employ machine learning approach.

Next, for the machine learning approach, our signal processing pipeline segments the data into one-second windows and we use 4 signals from the JINS MEME: EOG left (V_L), right (V_R), horizontal ($V_{horizontal}$) and vertical ($V_{vertical}$). Note that the horizontal and vertical of the EOG signals are derived from the combination of each side and bridge electrode, but horizontal and vertical signals are calculated by the left and right signals. We collected five trials per gesture for training and for the online test, we ran the classification every 30ms. We checked the maximum absolute values of V_L and V_R with threshold to distinguish gesture trials and used Random Decision Forest to classify gestures, as it was known to be fast and has low memory footprint [12]. We perform two types of classification on the data; one for classifying whether input has occurred and the other one for classifying the type of input (e.g., gesture left, right or horizontal).

We extracted 50 features in total from the four EOG signals, including 9 individual features from each signal and 14 combination features. These are common statistical features used when classifying time series data. The features are (i) deviation of FFT, (ii) root mean square, (iii) percentage of positive and (iv) negative values, (v) number of positive and (vi) negative peaks of original signal and (vii) root mean square, (viii) percentage of positive and (ix) negative values of the first difference between subsequent values of original signal. As the signal strength generated from gestures are not so significant, we also added combination features which are derived from two different sensor signals. For the combination features, we picked aggregation of root mean square values from two combinations left/right and horizontal/vertical electrodes, and we chose Pearson correlation coefficient value and the maximum cross-correlation value from all possible combinations of signals.

4.1 Gesture Recognition

Although we have not evaluated the system accuracy, our initial test shows promising result. It could recognize left/right gestures robustly, but not for up/down gestures. Therefore, we group both up/down gestures into a single vertical gesture (ignore direction). In total, we can robustly detect left, right and horizontal gestures (Figure 5), which is enough for basic interaction. For example, Google Soli radar in the Pixel 4 smartphone could only detect left, right and push gesture, yet it is enough for basic interaction.

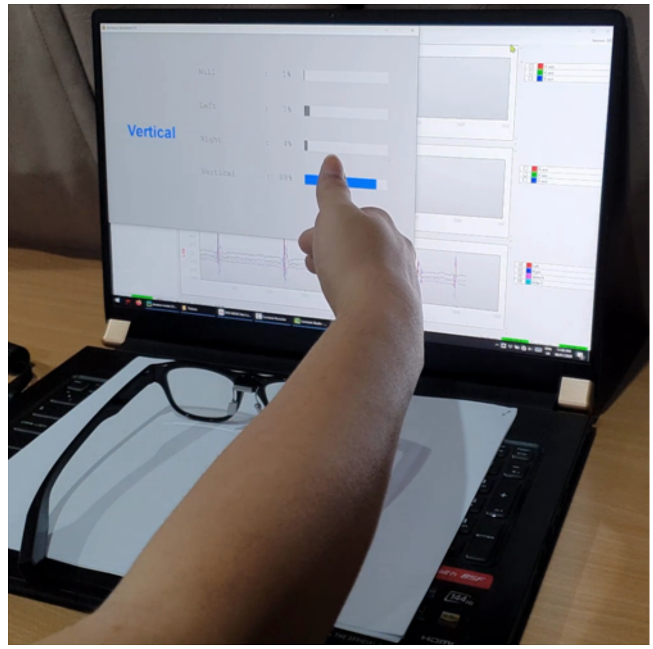

Figure 5: A demonstration of real-time midair gesture recognition using machine learning classifier. The JINS MEME smartglass is resting on a desk. The user performed a swipe gesture and is correctly detected as a vertical swipe.

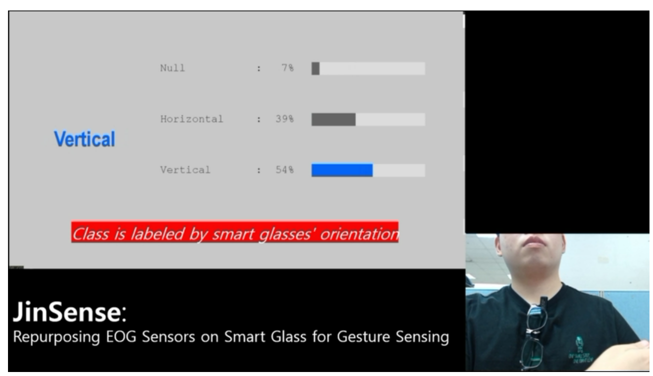

Figure 6: When the smart glass in placed in front pocket or collar, it becomes a gesture sensor to detect hand gestures on the go. In this case, the user swiped down using his hand, and the gesture is detected as vertical.

Based on our observation, other hand motions such as push, pull, rotate, wiggle also generate unique signal, as shown in Figure 3 and 4. We believe these gestures can be robustly detected with better machine learning technique that can extract better features, such as deep neural network, which we left for future work.

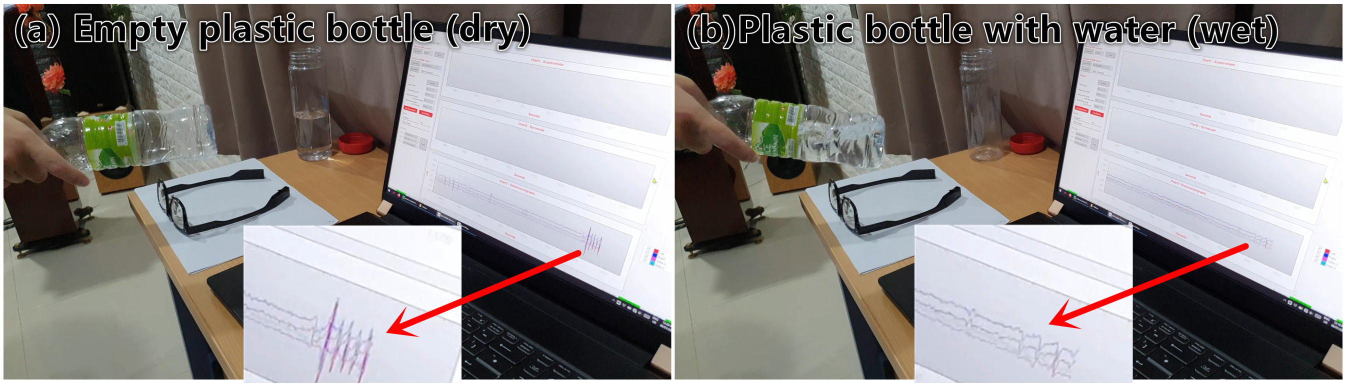

Figure 7: This figure shows the EOG signal (left) when an empty plastic bottle is moving on top of the sensor and (right) when a plastic bottle filled with water is moving on top of the sensor. The EOG signal clearly shows difference between the two conditions and the latter has a strong signal.

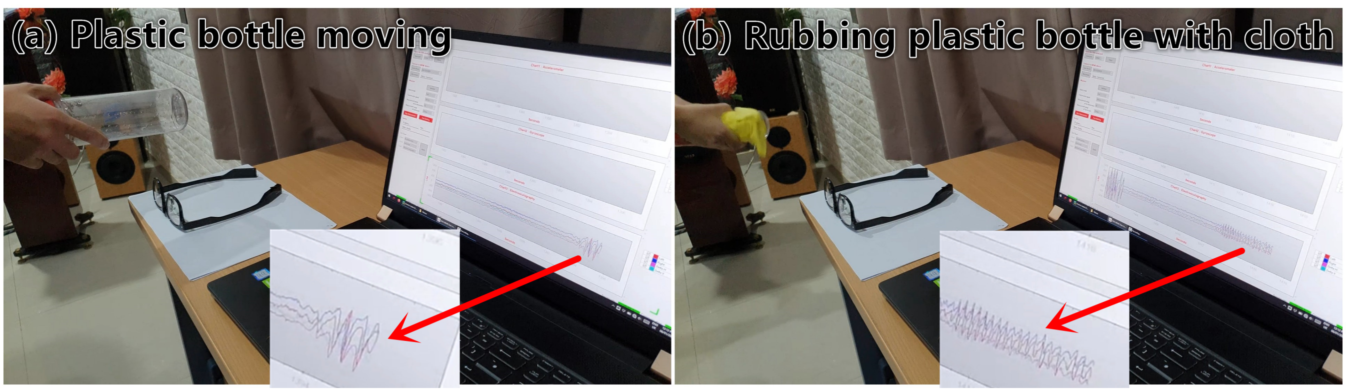

Figure 8: This figure shows the EOG signal (left) when a plastic bottle is moving on top of the sensor and (right) when the plastic bottle is rubbed with cloth from a long distance.

4.2 Proximity Sensing And Material Differentiation

In addition, our preliminary test also shows that it can potentially support human proximity sensing and material differentiation [20], as shown in Figure 7, 8 and video figure, although we have not thoroughly tested it. Our visualization clearly shows that the signal is unique and changing according to human proximity and different material moving around the sensor. Please refer to the video figure for demonstration. We are still in the process to collect more data and to train a robust recognizer to validate these claims.

In one example (Figure 7), an empty plastic bottle will generate signal with different amplitude when moved around the sensor, when compared to the same plastic bottle filled with water. Interestingly, the empty bottle causes the sensor to pickup a stronger signal with higher amplitude. With this, it might be possible to detect the water level of a container, or dryness of an object.

In another example (Figure 8), rubbing an empty plastic bottle from a long distance can still be detected by the EOG sensor (up to 1 meter in our test). The EOG signal shows unique pattern that can be leveraged for human action or activity recognition. We hypothesize this may be related to triboelectric effect or static electricity generated when rubbing cloth on plastic bottle.

In the video figure, we also show how different object and material when moved above the EOG sensor will cause the sensor to pickup different signal, which can be potentially used to differentiate object and material. In addition, human body moving around the eyewear also caused the sensor to pick up some signal, albeit rather weak. Again, more research and experiment have to be conducted to validate these claims.

5 APPLICATIONS AND USE CASES

While our approach may be limited to non-wearing situation only at the moment, we suggest a few compelling use cases and scenarios:

Interaction with IoT devices – Before going to bed, a person who wear glass usually removes the glass and put it on a bed-side desk. When she wakes up, she can perform different midair hand gestures to interact with devices, such as swipe to dismiss alarm, push to read out emails, wiggle to read out current time. In this scenario, users are not required pick up the phone and perform precise touch input, especially when the user is still sleepy.

Interaction while user is on-the-move -– When a user fold her sunglasses and put in the front pocket or collar (Figure 6), the eyewear turns into a front-facing gesture sensor for on-the-move interaction using simple hand motion. Users can perform a swipe gesture to dismiss notification, or to skip to next song.

Interaction with eyewear when it is docked — The eyewear can be left on an office desk or docked in car when not needed. Then it becomes a powerful gesture sensor for desktop environment or car infotainment input controller. Because the eyewear also supports proximity sensing, it can intelligently turn off a phone or monitor display to save battery when no human presence detected, similar to Google Pixel 4 presence sensing using radar.

Multi-purposes smart sensing -– Since the signals show difference when different materials are moved around the sensor, the system can be potentially used for material recognition, water level detection and dryness detection.

6 LIMITATIONS AND FUTURE WORK

Currently, we have not evaluated the system. In future work, we aim to evaluate the system by technical evaluation and user study.

While the user is wearing the device, because the electrodes are touching the skin directly, the EOG signal from eye motion and skin motion will be the primary source of signal and it is overshadowing the midair signal, making it difficult to extract useful features caused by midair motion. Thus our current sensing technique would not work while user is wearing the device. Potential solution could be multiplexing the sensor. We are also exploring ways to insulate the electrodes or to extend the area of electrodes to the outer frame of the glass using conductive material.

For future versions of the glasses it is possible to only focus on the electrodes part without the glass frame. The sensing apparatus can then be very small in size and therefore it can be easily attached on any device such as smartwatch, smartphone, smart speaker or home assistant (e.g., Google Home) to support midair gestures. It can be also attached on different body parts or apparels (e.g., button, belt), further enabling compelling use cases. The API makes it easy to prototype interaction and this may be a useful toolkit for the HCI and UbiComp research community as a whole.

Finally, we are exploring more compelling use cases that are uniquely enable by our sensing technique. This includes touchless interaction, discreet interaction and context-aware interaction.

7 CONCLUSION

In this work, we have explored new ways to exploit and repurpose existing EOG sensors on smart eyewear to achieve new sensing capabilities, such as midair gesture detection, human proximity sensing and material differentiation. Our preliminary explorations show that the technique is indeed working for gesture detection, and the captured EOG signals look promising for human proximity sensing and material differentiation. We believe this sensing technique will be useful because there is no need to add new sensors to a device such as smart eyewear, but instead it is possible reuse existing sensors for new capabilities.

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