Automated Data Gathering and Training Tool for Personalized "Itchy Nose"

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ABSTRACT

In "Itchy Nose" we proposed a sensing technique for detecting finger movements on the nose for supporting subtle and discreet interaction. It uses the electrooculography sensors embedded in the frame of a pair of eyeglasses for data gathering and uses machine-learning technique to classify different gestures. Here we further propose an automated training and visualization tool for its classifier. This tool guides the user to make the gesture in proper timing and records the sensor data. It automatically picks the ground truth and trains a machine-learning classifier with it. With this tool, we can quickly create trained classifier that is personalized for the user and test various gestures.

CCS CONCEPTS

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

KEYWORDS

Nose gesture; subtle interaction; EOG; wearable computer; smart eyeglasses; smart eyewear; Training tool; online classification; [1]

1 INTRODUCTION

Smart eyewears are becoming popular nowadays. These devices support speech recognition or using the touchpad on the device for getting inputs from the user. However, these actions can be disruptive, intrusive or socially unacceptable. Indeed, there are much related work on sensing the body gesture and use it as an input. In particular, "Itchy Nose" [6] is a system that can detect finger movements on the nose using electrooculography (EOG) sensor embedded in the frame of the eyeglasses. As mentioned in the paper, the gesture classifier requires personalized training for achieving better result. However, training takes much effort, especially on the data gathering and ground truth generation. For this reason, we propose a GUI based data gathering and automated ground truth generation and training tool to help and assist the personalized training process.

Figure 1 J!ns Meme and its EOG electrode placement.

2 RELATED WORK

There are various research work on detecting finger tapping on the body, such as the Skinput [3], TapSkin [9], and Earput [7]. Bragi Dash [2] is a pair of consumer earphones that supports a simple tapping gesture on the face. However, these techniques rely on rather a strong tapping, which would not be practical for the nose. Similarly, Bitey [1] explores tooth click gestures for hands-free interface control; Palpebrea Superioris [4] explores the design space of eyelid gestures; Eartouch [5] explores the ear as input surface, and CheekInput [8] explores the touch gestures on the

cheek as input. All of these works suggest that the human face can provide a rich medium for interaction with computing.
Finally, there is “Itchy Nose” [6] which use EOG sensor to detect finger tapping on the nose and can classify to five different gesture. It used a random decision forest classifier to classify different gestures with very high accuracy and robustness. Yet, the authors mentioned that it requires personal data to improve the accuracy.

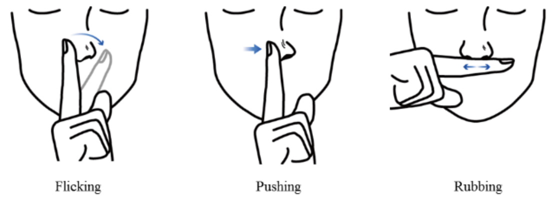

Figure 2: Three proposed input gestures of Itchy Nose.

3 SYSTEM

3.1 Itchy Nose

The EOG sensors in the J!ns Meme eyeglasses are strategically placed around the nose: two on the nose pads and one on the nose bridge. We stream raw data from the J!ins Meme over Bluetooth to a remote computer for real-time processing and classification. We implemented the system in Python with Pygame for visualization and Scikit-learn for training machine-learning classifiers. We use five signals from the J!ns Meme: EOG left, right, horizontal, vertical, and the z-axis of the gyroscope. In our last paper “Itchy Nose”, we used 10 features including five statistical features. We removed three non-dominant statistical features and modified standard deviation to the frequency domain. In result, we extracted 7 features for each signal: (i) root mean square, (ii) standard deviation of frequency domain, the number of (iii) positive, (iv) negative peak values (which are high on flick and rub), the numbers of values to cross a (v) positive threshold and (vi) negative threshold, and (vii) the largest number of values that exceed these thresholds consecutively. Also, we added the sum of all three axis values of the accelerometer and gyroscope to represent the average movement. In total, we used 51 features per signal window. For the classifier, we chose Random decision forest similar to our previous implementation due to its high accuracy and fast speed.

3.2 Training Tool

Following is the description of using the proposed automated tool. When we start using the tool, we have to type all the gestures name we want to train. For example, if we want to train same five gestures as in the previous paper, then we should type: left flick, left push, right flick, and right push. Those will be used when the system prompts the target gesture on the screen. After typing all the gestures, the system asks the users to press a button when they are prepared to perform the gesture. When the button is pressed, it countdowns three seconds and at the same time it shows the time left on the screen and makes a beep sound when the countdown ends. Then, we have to perform the target gesture within the next three seconds. As same with start countdown, it also countdowns to show when the recording ends. After the recording ends, we have to press a button to confirm that the input was correctly performed. If not, we can press the back button to do it again. Above descriptions are the one trial’s procedure, and the system shows 10 times per gesture in random order.
When all the gesture input trials are ended, it starts the training process. First, it picked one-second length from three seconds of the recording session. It picked the signal by counting the root mean square value of EOG signal, where it is most significant will be selected. After picking the true gesture data, it generates a false data which means there is no gesture. The false data is generated from the time window between start button pressed and recording start point, during the first countdown. After picking true and false data, it extracts features from each window and trains the random decision forest. When the training ends, it shows each gesture’s possibility and confidence on screen with bar plot that changes continuously in real-time. Hence, the user can try the gesture that was used in the training session and can distinguish whether the classifier works appropriately.

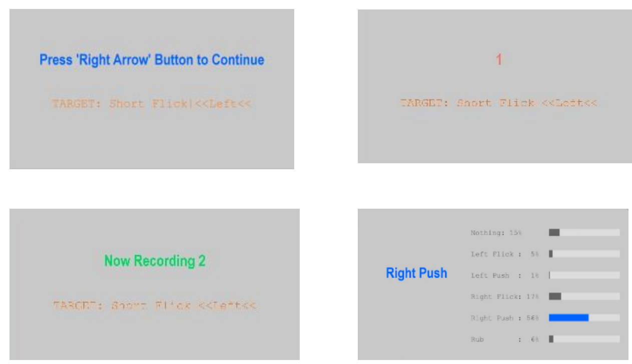

Figure 3: A graphical guide of data gathering and online classification screen after training.

4 CONCLUSIONS

Itchy Nose uses finger movements on the nose as input for interacting with a wearable computer. It may allow users to respond to notifications quickly without distracting nearby colleagues. With this tool, we can not only train and test the gesture for each person but also use various custom gesture such as wiggling or pinching with it.

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